The Dark Side of Asset Redeployability: Future Stock Price Crashes

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Abstract

There is tension underlying whether asset redeployability, which refers to the salability of the corporate capital assets of the firm, shapes crash risk. On one hand, greater asset redeployability engenders liquidity benefits that should enhance financial stability, thereby mitigating future stock price crash risk. On the other hand, asset redeployability enables managers to opportunistically exploit asset sales to engage in upward real earnings management in order to hide bad news, which, in turn, increases future stock crash risk. We find that, on average, asset redeployability is positively associated with stock price crash risk, suggesting that relying on redeployable assets to orchestrate upward real earnings undermines shareholders' interests. Reinforcing that real earnings management explains the positive association between asset redeployability and stock price crash risk, we find that this association is stronger for firms experiencing greater internal and external pressure to manage earnings. In additional evidence supporting the real earnings management channel, we find that asset redeployability is associated with a higher likelihood of just meeting or beating analyst forecasts, and recording of gains from asset sales. We contribute to extant research by providing evidence implying that asset redeployability has a dark side stemming from managers' incentives to suppress bad news, particularly when internal and external forces motivate them to manage real earnings upward.

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1. Introduction

In this paper, we analyze whether firm-specific stock price crash risk is sensitive to asset redeployability. Secondary markets for corporate capital assets are important for firms to be able to sell and buy corporate assets in response to their shifting liquidity needs, investment opportunities, and business strategies (Ramey and Shapiro, 2001; Schlingemann et al., 2002; Gavazza, 2010). Asset redeployability reflects the extent to which its capital assets can be liquidated at reasonable prices (Kim and Kung, 2017). Although the impact of a firm's asset structure on its financial stability remains an important question (Miller and Orr, 1966; Williamson, 1986; Anand and Singh, 1997; Wagner, 2007), empirical evidence on whether a core aspect of asset structure, asset redeployability, shapes financial stability remains scarce. Indeed, despite its importance, asset redeployability has attracted little attention outside the economics and finance literatures. In particular, extant accounting research seldom examines economic outcomes stemming from asset redeployability, including its effects on firms' financial stability. Accordingly, we extend prior research by examining the link between asset redeployability and the risk of future stock price crashes.[1] To the best of our knowledge, this relation has not been analyzed in previous literature, likely because firm-level data on asset redeployability have only become available recently (Kim and Kung, 2017).

Stock price crash risk refers to the tendency for firm-specific stock prices to drop

[1] The choice of stock price crashes as a proxy for financial stability stems from extant research documenting that firms that face liquidity problems or hide bad news experience an increasing likelihood of extreme negative stock price returns in the future (Clark and Weinstein, 1983; Hutton et al., 2009). In this paper, we argue that asset redeployability could be associated with extreme negative outcomes because of the link between asset redeployability and liquidity and the link between asset redeployability and the suppression of bad news.

significantly in a short period of time. Recent studies imply that the accumulation of bad news is the key factor that triggers stock price crash (e.g., Jin and Myers, 2006; Bleck and Liu 2007). Underlying this view is that managers possess more private information about the firm than outside investors. Due to various incentives such as compensation and career concerns (Kothari et al., 2009; Kim et al., 2011a), managers have a tendency to hoard bad news for an extended period of time, anticipating that it will ultimately disappear or be offset by subsequent good news. However, the amount of bad news a manager is willing or able to withhold is limited (Jin and Myers, 2006). When the accumulation of bad news eventually reaches a tipping point at which managers can no longer suppress the firm-specific negative information, it is suddenly revealed to the market at once, resulting in a stock price crash.

Extant theory and evidence provides competing predictions on the relation between asset redeployability and crash risk. In one direction, a major upside stemming from redeployable assets is that the sale of these assets can generate liquidity when the firm is experiencing resource constraints. It is important that the firm has sufficient liquidity to cater to its operational needs, as well as to meet its financial obligations (Opler et al., 1999; Dittmar et al., 2003; Bates et al., 2009). Consequently, from the perspective of liquidity demand, redeployability facilitates raising cash when liquidity needs arise, which, in turn, enhances the stability of the firm and reduces the likelihood of negative events occurring (Williamson, 1988; Shleifer and Vishny, 1992; Kim and Kung, 2017). It follows that the *liquidity* channel predicts a negative association between asset redeployability and stock price crash risk.

In the other direction, prior research implies that managers rely on selective corporate asset sales in orchestrating real earnings management designed to conceal bad news (e.g., Bartov, 1993; Black et al., 1998; Hermann et al., 2003). In particular, managers can choose to sell assets with unrealized gains to book an accounting profit. Graham et al. (2005) provide survey evidence suggesting that firms are eager to engage in real earnings management in striving to meet the market's earnings expectations, even if this practice undermines shareholder value. In fact, assets that can lead to a greater boost to the earnings number are more likely to be the firm's more productive assets that can be sold to other firms at a higher price. Real earnings management, compared to accruals-based earnings management, is likely to be not only costlier, but also more difficult to curtail (Cohen et al., 2008). To the extent that investors later become aware that the firm was withholding bad news and/or that firm value has fallen due to the loss in productive capacity, its stock may become more vulnerable to a crash (Jin and Myers, 2006; Hutton et al., 2009). Consequently, the *real earnings management* channel predicts a positive association between asset redeployability and stock price crash risk.

In a nutshell, there are two conflicting channels, *liquidity* and *real earnings management*, that makes the relation between asset redeployability and stock price crash risk an empirical question. Our primary purpose in this paper is to empirically clarify which channel dominates in shaping crash risk.

To examine the relation between asset redeployability and stock price crash risk, we rely on a new measure on asset redeployability developed by Kim and Kung (2017). Briefly, this firm-level measure is the value-weighted average of the industry-level redeployability index across business segments in which the firm operates; industry-level redeployability is evaluated using data from the Bureau of Economic Analysis (BEA) capital flow table.

In analyzing a large sample of U.S. firms covering the period from 1984 to 2015, we find that firms with higher asset redeployability are more likely to experience a future stock price crash. Reflecting its first-order economic materiality according to our coefficient estimates, crash risk increases by 5.5 percentage points with a one standard-deviation increase across the asset redeployability distribution. Our results are robust to specifying alternative asset redeployability measures, adding various controls, estimating random-effect panel regressions, and excluding financial crisis periods from the analysis. Our core evidence continues to hold in an instrumental variable framework that further dispels the endogeneity threat to reliable inference. Collectively, our evidence lends support to the intuition that the real earnings management channel, which involves managers selectively exploiting corporate asset sales to manage real earnings upward in order to suppress bad news, dominates the liquidity channel in shaping crash risk.

To shed further light on the real earnings management direction, we examine whether the relation between asset redeployability and crash risk varies in the cross-section. This analysis not only provides insights on the channel through which the documented relationship operates, but also strengthens identification given that this link is unlikely to arise if our measure of asset redeployability simply reflects unobserved economic forces; i.e., it would be hard to attribute this pattern of evidence to a competing explanation. We expect to observe that the positive impact of asset redeployability on stock price crash risk will be more pronounced in the presence of factors that exacerbate firms' real earning management. More specifically, we conduct a series of cross-sectional tests to examine whether the impact of asset redeployability on stock price crash risk varies systematically with internal and external performance pressure. Our evidence implies that the importance of asset redeployability to stock price crash risk rises for firms with high-power CEO equity incentives, firms with CEOs in the early and later in their tenure, and firms with overconfident CEOs. These results suggest that firms are more likely to use asset transactions to hide bad news when their CEOs face greater internal performance pressure. Additionally, we find that the impact of asset redeployability on stock price crash risk is concentrated in firms that have a large fraction of their shares held by transient institutional investors, firms that enjoy greater analyst coverage, and firms that exhibit relatively higher earnings response coefficients. These results are consistent with the narrative that managers with greater external short-term performance pressure from the stock market are more eager to suppress bad news using asset transactions, translating into a stronger link between asset redeployability and firm-specific crash risk. Importantly, this analysis reinforces the real earnings management view given that it would be difficult to attribute this pattern of evidence to an alternative explanation.

In additional analyses, we follow Hutton et al. (2009) by narrowing our focus to the post-Sarbanes-Oxley Act (SOX) period. In contrast to Hutton et al. (2009) who report that the positive association between financial reporting opacity crash vanishes after SOX, we find that the positive association between asset redeployability and crash persists afterward. This evidence reconciles with Cohen et al. (2008) in that real earnings management is not constrained and might even be exacerbated by SOX, which mainly tackles accruals-based earnings management.[2]

Next, we conduct validity tests on the intuition that higher asset redeployability is associated with upward real earnings management. To the extent that managers are indeed resorting to liquidating corporate assets in attempting to conceal bad news, we should observe patterns that support that firms with greater asset redeployability actively manage earnings upward. We initially examine the likelihood of a firm just meeting or beating analyst expectations (Bartov et al., 2002). Consistent with asset redeployability facilitating the use of asset liquidation to avoid disappointing the markets' expectations, we find that asset redeployability is associated with a higher likelihood of just meeting or

[2] It is important to stress that the financial reporting opacity measure under study in Hutton et al. (2009) essentially captures accruals-based earnings management to hide bad news. Our evidence that the positive relation between asset redeployability and crash remains after SOX helps reinforce that: (i) we are documenting a relation different from Hutton et al. (2009); and (ii) real earnings management to hide bad news plausibly explains the positive relation.

beating analyst expectations. We also find that asset redeployability increases the likelihood of selling assets that result in the recording of an accounting gain. In other words, our evidence suggests that firms do dispose of their assets to avoid reporting losses.

Our analysis contributes to extant research in several ways. First, we extend prior evidence on outcomes stemming from corporate asset sales and purchases. For example, Warusawitharana (2008) shows that increases (decreases) in profitability raise (reduce) the likelihood of asset purchases, and lower levels of liquid assets reduce the likelihood of asset sales. This literature focuses on the economic rationale (e.g., investment opportunities and agency problems) behind firms engaging in corporate asset transactions. Grounded in the historical-cost nature of accounting for corporate assets, we argue that earnings management motivations can persuade firms to undertake asset sales, which, in turn, can affect the stability of the firm. It is important to stress that *ex ante* asset redeployability appears to benefit firms by ensuring that they retain the flexibility to dispose of the assets when they are experiencing liquidity problems, thereby potentially enhancing firm stability. However, in responding to calls for evidence on the implications of firms manipulating real business activities (e.g., Xu et al., 2007; He and Tian, 2013), our analysis suggests that a dark side may accompany asset redeployability given that the sale of corporate assets may be undertaken to conceal bad news to the detriment of outside shareholders. Importantly, our analysis provides a more comprehensive picture of how a combination of business fundamentals, accounting rules, and managerial incentives can shape corporate outcomes.

Second, we contribute to research on real earnings management by considering whether firms resort to selling long-term assets in attempting to manage earnings upward (e.g., Bartov, 1993; Black et al., 1998; Hermann et al., 2003). Rather than focusing on firms' actual liquidation of assets, we examine the underlying nature of their asset structures in the form of asset redeployability. This *ex ante* approach facilitates analyzing the role that asset structure plays in the future stability of the firm evident in its stock price crash risk. Our evidence reconciles with theory demonstrating that real earnings management consumes economic resources and makes it difficult for investors to gauge underlying firm value from observing reported earnings (Wang, 2006).[3]

Third, we extend research on the determinants of stock price crash risk to include asset redeployability. Set against extensive prior evidence focusing on the importance of firm-level characteristics to stock price crash risk, we initiate research on the link between firms' asset structure and their crash risk. Investors naturally consider issues that affect future extreme returns (i.e., higher moment effects) to be highly relevant to their interests (e.g., Pan, 2002; Xing et al., 2010; Yan, 2011). After reporting evidence that firms are more likely to suffer a future stock price crash when asset redeployability is greater, we analyze whether this relation intensifies when internal and external forces exert more pressure on firms to manage real earnings upward.

Fourth, we extend emerging research on the consequences of asset redeployability. There is extensive economics and finance evidence on the role that asset redeployability plays in capital structure outcomes such as debt maturity (e.g., Benmelech, 2009), financing costs (e.g., Benmelech and Bergman, 2009; Ortíz-Molina and Phillips, 2014), and leverage (e.g., Campello and Giambona, 2013), or asset reallocation through mergers and trading in secondary markets (Almeida et al., 2011). In contrast, hardly any accounting research examines the economic implications stemming from asset redeployability. Taking

[3] It is important to stress at the outset that we focus on the implications of asset redeployability on stock price crash risk. Asset redeployability is not simply a proxy for earnings management as *ex ante* there are valid reasons to expect that it could be linked to various corporate actions/channels such as the sale of assets to generate cash when needed (an efficient use of asset redeployability that increases a firm's stability and lowers its crash risk), or the sale of assets to manage earnings upwards (an opportunistic use of asset redeployability to hide bad news, which later translates into higher crash risk).

advantage of firm-level data on asset redeployability that has only recently become available (Kim and Kung, 2017), we help close this gap by analyzing the impact of asset redeployability, which facilitates real earnings management, on future stock price crash risk. Cross-sectional analyses showing that this link intensifies when managers face more performance pressure reconciles with this earnings management explanation.

Finally, research on the role that asset redeployability plays in firm financial stability would naturally interest investors, policymakers, regulators, and managers. For example, our evidence that stock price crash risk rises with asset redeployability is relevant to investors eager to protect their interests. Firms exploiting asset redeployability not only facilitates the hoarding of bad news, but also it may undermine shareholder welfare by leading to lower future cash flows stemming from the loss of productive capacity.[4] Given that our evidence suggests that asset redeployability is partly responsible for the information asymmetry that engenders stock price crashes, our research implies that policymakers and regulators should closely monitor firms that exhibit higher asset redeployability, which provides insiders with wider scope to orchestrate real earnings management in order to conceal negative firm-specific information.

The rest of this paper is organized as follows. Section 2 reviews prior analytical and empirical research in developing the motivation for our predictions. Section 3 describes the data, variables, and summary statistics. Section 4 reports the main findings and Section 5 presents results from our cross-sectional analyses. Section 6 covers some additional analyses and Section 7 concludes.

2. Hypotheses Development

[4] As stressed earlier, the assets whose sales can most help in boosting earnings numbers are likely to be those that are more productive and command a higher price in secondary markets for corporate assets.

Asset redeployability refers to the salability of the capital assets of the firm. Prior research highlights two important features of the market for such assets: (i) there is an active secondary market for many corporate assets; and (ii) there is ample variation in asset redeployability within and across industries (Warusawitharana, 2008; Kim and Kung, 2017). Kim and Kung (2017) find that after an increase in uncertainty, firms having more redeployable capital assets reduce investment less, consistent with theory linking asset redeployability to investment irreversibility (i.e., the wedge between purchase and liquidation values of the assets). Additionally, they document that more redeployable assets exhibit higher recovery rates and are traded more actively in secondary markets.

From an economic standpoint, an important consequence of asset redeployability is the liquidity that the assets bring, especially in times when a firm requires cash for servicing its financial obligations. Prior studies analyzing the impact of the liquidity of a firm's assets in terms of financial stability have typically focused on its current assets. In his seminal research on the predictors of bankruptcy, Altman (1968) shows that the liquidity of short-term assets, measured as working capital scaled by total assets, is a major determinant of bankruptcy. Subsequent evidence corroborates the stability benefits stemming from having more liquid current assets (e.g., Ohlson, 1980; Campbell et al., 2008; Campello et al., 2011).

Asset redeployability relates to the liquidity of non-current (i.e., capital) assets. Williamson (1988) argues that given that redeployable assets have high liquidation values, they can facilitate arranging debt financing. Also, in the event that the firm cannot service its debts, creditors can seize the assets and redeploy them, making creditors less likely to pursue adverse actions when the firm begins to exhibit financial distress. A number of studies focus on the expected stability of firms attributable to the liquidity of redeployable assets when examining the capital structure outcomes of asset redeployability. For example, Benmelech (2009) finds that firms' asset redeployability affects both the amount and the maturity structure of their debt. Reinforcing its liquidity benefits, Campello and Giambona (2013) find that greater asset redeployability facilitates borrowing for firms that are more likely to face credit frictions, especially during periods when credit is tight. Ortíz-Molina and Phillips (2014) report that firms with more redeployable assets enjoy cheaper financing costs. Overall, redeployable assets may help stabilize firm business operations, potentially lowering the incidence of negative events (e.g., project failure due to high cost of capital, or financial distress due to inadequate cash to repay debt) and hence future stock price crash risk.

From an accounting perspective, assets that are redeployable provide opportunities for managers to engage in real earnings management via asset sales that can facilitate the hoarding of negative information. Prior research documents that firms engage in various forms of real earnings management ranging from cutting expenditures (e.g., Roychowdhury, 2006) to selling securities and capital assets to recognize unrealized gains (e.g., Ellul et al., 2015; Bartov, 1993; Hermann et al., 2003). Real earnings management involving asset sales is most relevant for our purposes. Bartov (1993) finds that income from corporate asset sales is significantly higher for firms with decreasing earnings before income from asset sales and are clustered in the fourth fiscal quarter, consistent with managers choosing the timing of asset sales to manage earnings upward. Hermann et al. (2003) report that managers of Japanese firms generate income from sales of corporate assets and marketable securities in order to meet their earnings guidance.

Similarly, anecdotal evidence reinforces that firms exploit asset sales in their real earnings management activities. For example, a February 16, 2002 article in *The Globe and Mail* recounts that IBM used the $300 million in proceeds from the disposal of one of its operating units to add about 8 cents per share to fourth quarter earnings, resulting in IBM beating analyst forecasts by 1 cent (Scott, 2014: 185). The same article mentioned that IBM's share price fell by 4% due to the revelation of IBM's actions. A follow-up article in the same newspaper criticized IBM for its creative accounting.[5] The Securities and Exchange Commission (SEC) later opened a preliminary inquiry into IBM's accounting practices and noted that IBM had claimed that the reason for higher operating earnings was due to tight cost controls, as opposed to proceeds from the sale of its assets. Although the inquiry was later suspended, the SEC issued a bulletin reminding firms to report gains or losses on asset sales separately in their financial statements.

Assets whose sale can have a large impact on earnings are more likely to be the more productive assets for which other firms are willing to pay a higher price.[6] It follows that real earnings management via asset sales can be very costly to shareholders, especially relative to accruals-based earnings management (Cohen et al., 2008). For example, in striving to meet short-term earnings expectations, managers could sell assets valuable for the long-term future of the firm. In a survey of U.S. chief financial officers (CFOs), Graham et al. (2005) report that a majority of CFOs indicate that they are willing to sacrifice long-term value to meet market expectations of short-term earnings targets due to their own wealth, career, and external reputation concerns. Accordingly, to the extent that greater asset redeployability enables managers to undertake asset sales to help suppress bad news, asset redeployability may be positively associated with stock price crash risk.

In short, there are reasons to expect that we will observe a positive (negative)

[5] http://www.theglobeandmail.com/report-on-business/ibm-critics-expect-reckoning-on-firms-creative-accounting/article25292004/

[6] For example, assume three machineries each with a book value of $2 million. Further assume that the market values of the machineries are $1 million, $3 million, and $5 million because of difference in productivity. To manage earnings upwards, selling the least productive machinery will be counterproductive because it will result in a loss of $1 million. Selling the most productive machinery will have the largest impact on earnings because it will result in a gain of $3 million, although this disposal will also negatively affect the firm's productive capacity to its longer-term detriment.

relation between asset redeployability and stock price crash risk under the real earnings management (liquidity) channel. Although there is tension underlying this research question, we predict, on balance, that firms with more redeployable assets tend to experience more stock price crash risk (all hypotheses are stated in the alternative):

H_1: Asset redeployability is positively related to stock price crash risk.

Prior research implies that performance pressure is a major determinant of earnings management. This pressure can arise from either internal forces, particularly incentives facing top management, and external forces given the emphasis that stakeholders place on firm earnings. We expect to observe that, to the extent that real earnings management indeed explains the positive association between asset redeployability and stock price crash risk, this association would be stronger under conditions where there is greater pressure to manage earnings upward.

In initially focusing on the role of internal pressure that the CEO experiences, we consider three drivers of this pressure, namely, CEO equity compensation, CEO tenure, and CEO overconfidence. Extensive prior research suggests that managers have incentives to manage earnings upward to increase their equity compensation. Cheng and Warfield (2005) find that managers with greater equity incentives are more likely to report earnings that meet or just beat analysts' forecasts in order to increase the value of their shares. Bergstresser and Phillippon (2006) find that firms with CEOs whose overall compensation is more sensitive to company share prices exhibit more earnings management. Kim et al. (2011a) document that executive equity compensation incentives are positively associated with firm future stock price crash risk.

Concerning CEO tenure, Dechow and Sloan (1991) show that CEOs in their final years in office slash R&D spending, consistent with incentives to increase reported earnings to maximize compensation given their short employment horizon. Kalyta (2009) finds that

CEOs tend to engage in income-increasing earnings management in the pre-retirement period when their pension plans are based on firm performance. Further, Ali and Zhang (2015) show that CEOs tend to overstate firm earnings more in their early years of tenure to favorably influence the market's perception of their ability.

Moreover, Malmendier and Tate (2005; 2008) suggest that overconfident CEOs tend to overestimate the future cash flows of investment projects and their ability to control the performance of these projects. To avoid intervention by "impatient" investors, overconfident CEOs are reluctant to disclose privately observed negative feedback about the projects and even manipulate accounting disclosure to convey their optimistic beliefs about the projects' prospects (Kim et al., 2016). Schrand and Zechman (2012) document that overconfident executives are more likely to exhibit an optimistic bias, leaving them more susceptible to start on a slippery slope toward financial misreporting. In particular, they find evidence supporting that optimistic bias leading to an increased likelihood that the manager intentionally exaggerates earnings in later years, culminating in the firm becoming subject to a SEC Accounting and Auditing Enforcement Release (AAER). This discussion motivates our next prediction:

H_{2a}: The positive relation between asset redeployability and stock price crash risk is greater when managers experience more internal pressure to hide bad news.

Next, we consider the moderating role that pressure applied by outside stakeholders plays. Specifically, we focus on three drivers of this pressure, namely, transient institutional investors, financial analysts, and earnings-related stock price pressure. First, prior research implies that different types of institutional investors can exert different pressure on managers to engage in earnings management. Transient institutional investors are institutions with high portfolio turnover, highly diversified portfolio holdings, and strong interests in short-term trading profits (Bushee, 1998). Porter (1992) argues that transient institutions favor short-term price appreciation and exit in response to poor earnings. Bushee (1998; 2001) documents that transient institutions prefer firms with greater expected short-term earnings, which makes managers overly short-term focused. Matsumoto (2002) finds that management's incentives to avoid negative earnings surprises is greater for firms with higher transient institutional ownership, as revelation of negative earnings surprises may lead to their large-scale exit.

Second, financial analysts are perceived by managers to be one of the most important groups that affects stock price of their firms (Graham et al., 2005). Analyst forecasts are a primary earnings target that managers strive to meet given that failure to do so may lead to significant declines in stock prices (Degeorge et al., 1999). As a key aspect of the job of analysts is to forecast near-term earnings and make corresponding stock recommendations, they might impose excessive performance incentives on managers to focus intently on the short-run. For example, Burgstahler and Eames (2006) find that firms manage earnings upwards to avoid reporting earnings lower than analysts' expectations. He and Tian (2013) attribute their evidence that firms covered by more analysts are less innovative to analysts overly pressuring managers toward achieving short-term goals at the expense of focusing on long-term innovative projects. Huang et al. (2017) report a positive relation between analyst coverage and whether a firm meets or beats analyst forecasts, suggesting that greater analyst coverage raises the pressure on managers to meet short-term performance targets.

Finally, we examine whether the role that asset redeployability plays in crash risk hinges on earnings-related stock price pressure. An adverse consequence of missing market expectations is the tendency for firms to experience large declines in their stock prices (e.g., Bartov et al., 2002; Skinner and Sloan, 2002). Managers naturally prefer to avoid stock price declines given its negative implications evident in managerial compensation (Bushman and Indjejikian, 1993), managerial turnover (Warner et al., 1988), and lawsuits by shareholders (Kellogg, 1984; Lev and Villiers, 1994). Moreover, the adverse impacts could extend to contracts involving various stakeholders (e.g., creditors, customers, suppliers, and employees) who are concerned about the financial condition of the firm (Opler and Titman, 1994).[7] When the market is highly responsive to earnings surprises, managers have stronger incentives to inflate earnings because any negative unexpected earnings will lead to a large drop in stock prices. Accordingly, to the extent that stock prices are more sensitive to earnings news, we expect that stock price pressure on the managers to engage in earnings management to be greater, leading to our final prediction:

H_{2b}: The positive relation between asset redeployability and stock price crash risk is greater when managers experience more external pressure to hide bad news.

3. Data and Variables

3.1. Sample

Our initial sample is comprised of firms at the intersection of the asset redeployability data from Kim and Kung (2017), financial data from Compustat, and stock return data from the Center for Research in Security Prices (CRSP). The analysis starts in 1984 because this is the first year for which asset redeployability data is available. We follow Kim et al. (2011a; 2011b) by excluding observations with negative book value of equity, with year-end stock prices less than \$1, or with fewer than 26 weeks of stock return data. Similarly, we exclude observations with insufficient information for constructing the crash risk measures, and those with missing values for other regression variables. We winsorize all variables (except for dummy variables) at both the 1st and 99th percentiles to mitigate the impact of outliers and database coding errors. After imposing these screens, we are left with a final sample consisting of 99,968 firm-year observations for 12,110 unique

[7] For example, Merton's (1974) model uses the market value of a firm's equity in calculating a firm's default risk and captures the notion that market prices contain forward-looking information suited for determining likelihood of default. See also Hillegeist et al. (2004) and Vassalou and Xing (2004).

firms during the period 1984-2015.

3.2. Stock Price Crash Risk Measure

After recent research (e.g., Chen et al., 2001; Hutton et al., 2009; Chang et al., 2017), we proxy for stock price crash risk using two measures: the crash dummy (*CRASH*) and negative skewness (*NSKEW*). Both measures are based on firm-specific weekly returns estimated by the residual return from the following expanded market model:

$$r_{i,t} = \beta_0 + \beta_1 r_{mkt,t-2} + \beta_2 r_{mkt,t-1} + \beta_3 r_{mkt,t} + \beta_4 r_{mkt,t+1} + \beta_5 r_{mkt,t+2} + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the return on stock i in week t, $r_{mkt,t}$ is the return on the CRSP value-weighted market index, and $\varepsilon_{i,t}$ is the error term. We include the lead and lag market index returns to account for non-synchronous trading (Dimson, 1979). Following prior research (e.g., Chen et al., 2001; Hutton et al., 2009), we estimate the firm-specific weekly return, $W_{i,t}$, as the natural logarithm of one plus the regression residual (i.e., $W_{i,t} = \ln(1+\varepsilon_{i,t})$).

Our first measure of crash risk, the crash dummy, is an indicator variable that equals one for a firm that experiences one or more crash weeks during a fiscal year, and zero otherwise. We follow Hutton et al. (2009) by defining crash weeks as those for which a firm experiences firm-specific weekly returns that are 3.09 standard deviations below the mean firm-specific weekly returns over the fiscal year. The number 3.09 is chosen to generate a 0.1% frequency in the normal distribution.

Our second measure of crash risk, negative skewness, is calculated by taking the negative value of the third moment of firm-specific weekly returns during the fiscal year, scaled by the standard deviation of firm-specific weekly returns raised to the third power. Specifically, for each firm i in year t, we calculate negative skewness as:

$$NSKEW_{i,t} = -[n(n-1)^{3/2} \sum W_{i.t}^3] / [(n-1)(n-2)(\sum W_{i,t}^2)^{3/2}] \tag{2}$$

where n is the number of observations of firm-specific weekly returns during fiscal year t.

Higher values of negative skewness indicate a more left-skewed distribution of stock returns, reflecting a higher likelihood of stock price crash.

3.3. *Asset Redeployability Measure*

We employ the asset redeployability data from Kim and Kung (2017).[8] They construct the measures using the 1997 BEA capital flow table, which breaks down expenditures on new equipment, software, and structures by 180 assets for 123 industries in the BEA table. Kim and Kung (2017) derive firm-level asset redeployability measures for each firm in each year using a three-step procedure.

In the first step, Kim and Kung (2017) specify an asset's redeployability score as the sum of weights of industries that use the asset among the 123 BEA industries. Industry weight is calculated using market capitalization of Compustat firms in each BEA industry. In the second step, the authors take the value-weighted average of the asset-level redeployability scores across the 180 assets in the BEA table to generate an industry-level asset redeployability index. The weight is each industry's expenditure on a particular asset divided by its total capital expenditure from the BEA table. In the last step, Kim and Kung (2017) construct the firm-level asset redeployability measure as the value-weighted average of the industry-level redeployability index across business segments in which the firm operates. The weight is the proportion of each business segment's sales over the firm's total sales. Business segment sales data is obtained from Compustat segment files. If segment data is missing for a firm-year, Kim and Kung (2017) impute the firm-level asset redeployability measure from industry-level measures based on the firm's industry classification in Compustat.

3.4. *Control Variables*

[8] The data is available from Hyunseob Kim's website at http://blogs.cornell.edu/hyunseobkim/, and Howard Kung's website at https://sites.google.com/site/howardpkung1/

In the estimations, we include several control variables to account for other determinants of stock price crash risk. Return volatility (*SIGMA*) is the standard deviation of firm-specific returns, as firms with more volatile stock returns are likely to be more crash prone. Stock return (*RET*) is the average weekly return during the year. We include past returns because Chen et al. (2001) document that past returns have predictive power for future crash risk. Stock turnover (*DTURN*) is the de-trended average monthly turnover rate of the stock, which proxies for differences of opinion among investors and has been shown to be positively related to future crash risk (Chen et al., 2001). To control for the size and growth effects on future crash likelihood, we include firm size (*SIZE*), calculated as the natural log of market capitalization, and market-to-book (*MB*), calculated as the market value of equity divided by the book value of equity. Leverage ratio (*LEV*) is calculated as long-term debt divided by total assets. We include leverage ratio given its potential negative association with future crash risk (Kim et al., 2011a). Return on assets (*ROA*) reflects past firm performance, measured as income before extraordinary items scaled by lagged total assets. Additionally, we control for abnormal accruals (*ABN_ACC*), measured by the absolute value of discretionary accruals calculated following Dechow et al. (1995). We also control for abnormal expenses (*ABN_EXP*), measured by abnormal product costs minus abnormal discretionary expenses, both of which are calculated following Roychowdhury (2006) and Cohen and Zarowin (2010). Finally, we control for lagged negative skewness since Chen et al. (2001) find that stock return skewness is persistent over time.

3.5. Descriptive Statistics

Table 1 presents the summary statistics for the regression variables. The table shows that the mean value of the crash dummy is 0.185, suggesting that 18.5% of the sample firms experience one or more crash weeks during the fiscal year. The mean value of negative skewness is -0.057, indicating a slightly positively skewed firm-specific return distribution in our sample. The statistics for the stock price crash risk measures fairly closely resemble those reported in prior research (e.g., Hutton et al., 2009; Kim et al., 2011a; 2011b; Chang et al., 2017). Finally, the mean (median) value of asset redeployability is 0.399 (0.409). The summary statistics for the control variables are largely consistent with prior studies as well.

[Insert Table 1 here]

Table 2 presents the Pearson correlations between the variables in the regression analysis. This includes that the two cash risk measures, the crash dummy and negative skewness, are highly correlated (0.607), suggesting that the two measures capture similar underlying constructs. Further, asset redeployability is positively correlated with both stock price crash risk measures (0.013 for the crash dummy and 0.017 for negative skewness). Although this provides univariate evidence implying a positive association between asset redeployability and stock price crash risk, we evaluate in the next section whether this result holds in a multivariate framework.

[Insert Table 2 here]

4. Empirical Results

4.1. Baseline Regression

In this section, we perform multivariate regression analysis on the relation between asset redeployability and stock price crash risk. We follow prior research in estimating these models (e.g., Hutton et al., 2009; Kim et al., 2011a; 2011b; Chang et al., 2017):

$$\begin{aligned} CRASH_{i,t} &= \beta_0 + \beta_1 AR_{i,t-1} + \beta_2 NSKEW_{i,t-1} + \beta_3 SIGMA_{i,t-1} + \beta_4 RET_{i,t-1} \\ &+ \beta_5 DTURN_{i,t-1} + \beta_6 SIZE_{i,t-1} + \beta_7 MB_{i,t-1} + \beta_8 LEV_{i,t-1} + \beta_9 ROA_{i,t-1} \\ &+ \beta_{10} ABN\_ACC_{i,t-1} + \beta_{11} ABN\_EXP_{i,t-1} + Yr_t + \varepsilon_{i,t} \end{aligned} , \quad (3)$$

$$
\begin{aligned}
NSKEW_{i,t} &= \beta_0 + \beta_1 AR_{i,t-1} + \beta_2 NSKEW_{i,t-1} + \beta_3 SIGMA_{i,t-1} + \beta_4 RET_{i,t-1} \\
&+ \beta_5 DTURN_{i,t-1} + \beta_6 SIZE_{i,t-1} + \beta_7 MB_{i,t-1} + \beta_8 LEV_{i,t-1} + \beta_9 ROA_{i,t-1} \\
&+ \beta_{10} ABN\_ACC_{i,t-1} + \beta_{11} ABN\_EXP_{i,t-1} + Yr_t + \varepsilon_{i,t}
\end{aligned}
\quad , \qquad (4)
$$

where i denotes the firm, t denotes the year, Yr_t denotes the year fixed-effects, and $\varepsilon_{i,t}$ is the error term. We estimate equation (3) using logit and equation (4) using ordinary least squares (OLS). The *z*- or *t*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. We adopt the industry classification in the BEA table in clustering standard errors. Since all of the independent variables are lagged by one year, the sample size for the tests is reduced to 84,964 firm-year observations.

The baseline regression results are reported in Table 3. In Column (1) where we focus on the crash dummy, the coefficient on asset redeployability is positive and highly statistically significant (*z*-statistic=2.729), implying that firms with higher asset redeployability are more likely to experience a future stock price crash. The marginal effect of asset redeployability on the crash dummy (evaluated at the mean values of the independent variables) is 0.096, suggesting that a one-standard-deviation increase in asset redeployability (0.105) leads to an increase in crash probability of 0.096*0.105=1.01%. This is 5.5 percentage points compared to the sample mean of the crash dummy (18.5%), reflecting that the impact of asset redeployability on stock price crash risk is also economically material.

In Column (2), we tabulate the evidence after specifying negative skewness as the dependent variable. Reinforcing the crash dummy-based results, the coefficient on asset redeployability loads highly positively (*t*-statistic=2.715). In terms of economic significance, a one-standard-deviation increase in asset redeployability (0.105) raises negative skewness by 0.112*0.105=0.012. Overall, we provide strong, consistent evidence supporting the hypothesis that high asset redeployability enables managers to hide bad news through asset transactions, which leads to the stockpiling of bad news and subsequent stock price crash.

The results for the control variables are largely consistent with recent research (e.g., Hutton et al., 2009; Kim et al., 2011a; 2011b; Chang et al., 2017). More specifically, stock price crash risk is positively associated with return volatility, stock return, stock turnover, firm size, market-to-book, return on assets, and accruals earnings management, while negatively associated with the leverage ratio. Untabulated results show that the largest variance inflation factor (VIF) is 1.476, which is below 5, dispelling concerns surrounding multi-collinearity in our setting (O'Brien, 2007).

[Insert Table 3 here]

4.2. Robustness Checks

In this section, we conduct several robustness checks to evaluate whether our baseline results are materially sensitive to model re-specification. For the sake of brevity, we only report the coefficient on asset redeployability in the analysis in Table 4.

First, we re-estimate the regressions after replacing the asset redeployability measures. In the baseline analysis, we employ the asset redeployability measure calculated based on an asset-level redeployability score that uses market capitalization of Compustat firms in each BEA industry-year as the weight. In this section, we use the modified version of the measure which incorporates correlation of outputs among firms within industries. We also adopt the asset redeployability measure calculated based on the asset-level redeployability score that uses the equal weight for each BEA industry-year. The results are presented in Panel A of Table 4, which show that the coefficient on asset redeployability remains positive and statistically significant (smallest z- or t-statistic=2.347). This evidence suggests that our core findings persist under alternative asset redeployability measures.

Second, we consider alternative firm-specific thresholds in defining crash weeks. In the baseline regression, we define crash weeks as those weeks during which a firm experiences firm-specific weekly returns that are 3.09 standard deviations below the mean firm-specific weekly returns. In this section, we alter the threshold to 4 standard deviations below the mean firm-specific weekly returns in defining the crash dummy. We also use a general instead of a firm-specific threshold to identify crash weeks, as a firm-specific threshold might be subject to the concern that it is not economically significant enough to be a crash for stocks with low volatility. For this analysis, we specify crash weeks as those weeks during which a firm experiences firm-specific weekly returns that are below -15%. We report these results in Panel B of Table 4, which include that the coefficient on asset redeployability remains positive and statistically significant (smallest *z*- statistic=2.876). This evidence collectively implies that our core results hold under alternative firm-specific thresholds in defining crash weeks.[9]

Finally, we construct stock price crash measures using firm-specific returns so that the crashes are largely firm-specific events. However, it is still likely that market-wide economic shocks affect both individual firms and industry asset redeployability, which results in the association between asset redeployability and stock price crash. Although including year fixed effects in the regressions alleviates this concern, we also analyze whether our evidence is sensitive to confronting this issue by excluding the financial crisis periods (i.e., this involves removing observations from 1987, 2000-2002, and 2007-2008 in successive regressions). Reassuringly, the results reported in Panel C of Table 4 include that the coefficient on asset redeployability remains positive and statistically significant (smallest *z*- or *t*-statistic=2.226) when we narrow our focus to the non-crisis years. These results suggest that our findings are not driven by market-wide economic shocks.

[9] Similarly, the results continue to hold when we use 3.5 standard deviation, 4.5 standard deviation, -10%, and -20% as the threshold in defining crash weeks.

[Insert Table 4 here]

4.3. Endogeneity Tests

Since asset redeployability is measured at the industry level, it is less likely that firm-specific stock price crash has a material impact on asset redeployability in the whole industry, implying that reverse causality is less of a threat to reliable inference in our setting. However, there is still some concern that asset redeployability and stock price crash risk are correlated with variables omitted from the regressions, spuriously driving our findings. In this section, we conduct three tests to tackle this concern.

First, we add several controls that reflect determinants of stock price crash risk according to prior research. These variables include tax avoidance (Kim et al., 2011a), managerial equity incentives (Kim et al., 2011b), religious adherence (Callen and Fang, 2015), accounting conservatism (Kim and Zhang, 2016), CEO overconfidence (Kim et al., 2016), and stock liquidity (Chang et al., 2017). We further control for the financial constraints index proposed by Hadlock and Pierce (2010), and firms' information environment proxied by analyst forecast dispersion (Johnson, 2004) and auditor industry specialization (Dunn and Mayhew, 2004). Although adding these controls to the regressions is responsible for serious data attrition (i.e., data constraints lead to the sample size falling steeply to 12,269 firm-year observations), we continue to find that asset redeployability enters positively (at the 5% level) in both regressions in Panel A of Table 5 despite the loss in power.

Second, we estimate random-effects regression models to further mitigate the omitted variable concerns. This method assumes that the variation across firms is random and uncorrelated with the independent variables in the regression model. An advantage of random-effects regression is that it allows for time-invariant variables in the regression. Since stock price crash is not a common event, the dependent variables in our setting are largely time-invariant. Accordingly, random-effects estimation better suits the data than would a fixed-effects regression model. The results are presented in Panel B of Table 5. The regression in Column (1) is performed by random-effect Logit model and the regression in Column (2) is performed by random-effect panel regression. In both regressions, the coefficient on asset redeployability remains positive and statistically significant at the 1% level, lending additional support that potential omitted variable bias is not behind our core evidence.

Last, we further address the endogeneity issue using an instrumental variable approach despite the standard difficulty in identifying strong, valid instruments. In the spirit of recent research involving selecting an instrumental variable (e.g., Laeven and Levine, 2009; Lin et al., 2013; Boubaker et al., 2017), the instrumental variable we specify is the historical industry asset structure.[10] First, we identify the first year each firm appears in our sample. Then, we calculate the historical industry asset redeployability as the average asset redeployability of other firms in the same primary industry during that year. The initial average asset redeployability in a firm's industry is a suitable instrument for the firm's asset redeployability given that an individual firm's asset structure is correlated with its industry average but it is unlikely that an individual firm's stock price crash risk is directly driven by the historical industry average asset structure other than through its effect on the firm's own asset structure. The regression results are presented in Panel C of Table 5. In the panel, we report in Column (1) the results of the first-stage regression in which asset redeployability is the dependent variable. The results show that the coefficient on historical industry asset redeployability is positive and statistically significant (*t*-statistics 10.474). Partial *F*-statistic (untabulated) suggests that historical industry asset redeployability explains a significant portion of variation in asset redeployability in our

[10] These studies rely on the initial industry average ownership structure to instrument for the firm's ownership structure, while we use the initial industry average asset structure to instrument for the firm's asset structure.

sample. Further, historical industry asset redeployability is unlikely to have a direct impact on firm-specific crash risk. It follows that historical industry asset redeployability is a valid instrument in our setting (Larcker and Rusticus, 2010).

We adopt the standard two-stage least squares (2SLS) regression for negative skewness. However, we are unable to use the same approach for the crash dummy because the standard 2SLS regression will yield biased estimates if the dependent variable is a dummy variable (Wooldridge, 2002). Instead, we follow Wooldridge (2002) by using the predicted value of asset redeployability from Column (1) as an instrumental variable in a standard instrumental regression. The results are presented in Columns (2) and (3) of the panel. In both cases, the coefficient on instrumented asset redeployability is positive and statistically significant (smaller *z*- or *t*-statistics 3.069), helping to mitigate the endogeneity threat.

[Insert Table 5 here]

5. Cross-Sectional Tests

5.1. The Role of Internal Performance Pressure

We deepen our analysis by examining whether the impact of asset redeployability on stock price crash risk varies systematically with internal performance pressure. We focus on the role of three internal performance pressure measures, including CEO equity incentives, CEO tenure, and CEO overconfidence. As stressed earlier in Section 2, we expect to observe that the importance of asset redeployability to stock price risk to be larger for firms with high CEO equity-based compensation, firms with CEO in the early and later years of their tenure, and firms with overconfident CEO.

After Kim et al. (2011a), we calculate CEO equity incentives (*CEO_INCT*) as the ratio of the CEO's equity compensation pay-performance-sensitivity over the sum of equity compensation pay-performance-sensitivity, salary and bonus in each year. CEO tenure (*CEO_TNR*) is defined as a dummy variable equal to one if the CEO is in the first three years or the last year of his/her tenure, and zero otherwise. Further, we follow Malmendier and Tate (2005; 2008) by measuring CEO overconfidence (*CEO_CONFI*) as a dummy variable equal to one for all years after a CEO holds options that are at least 67% in the money, and zero otherwise. Data used to calculate the three measures are obtained from Compustat's ExecuComp database.

To test the impact of internal performance pressure on the relation between asset redeployability and stock price crash risk, we interact asset redeployability with each measure and integrate the interaction term into the regression specifications in equations (3) and (4). The results are presented in Table 6. Columns (1) and (2) show that the coefficient on the interaction term between asset redeployability and CEO equity incentives is positive and statistically significant (smaller *z*- or *t*-statistics 2.27), suggesting that the effect of asset redeployability on stock price crash is stronger when the CEO has a high proportion of equity incentives. In Columns (3) to (6), we report the results for CEO tenure and CEO overconfidence, which implies that the impact asset redeployability on stock price crash is stronger when the CEO is in their early years or last year of tenure, or when the CEO is overconfident. These results are consistent with the intuition that managers are more likely to exploit asset transactions to conceal bad news when they face greater internal performance pressure (i.e., their motivation for hoarding bad news through asset transactions is higher).

[Insert Table 6 here]

5.2. The Role of External Performance Pressure

Similar to internal performance pressure, external performance pressure from the stock market may also affect managers' incentives to hide bad news through asset transactions. We employ three measures of stock market performance pressure, namely, transient institutional ownership, analyst coverage, and the earnings response coefficient. Transient institutional investors are institutions with high portfolio turnover, highly diversified portfolio holdings, and strong interests in short-term trading profits (Bushee, 1998). Bushee (1998) finds that firms with more transient institutional investors myopically cut R&D investment to hide earnings declines. Cutting R&D investment is a form of upward real earnings management (Roychowdhury, 2006). We calculate transient institutional ownership (*TRAIO*) as the number of shares held by transient institutions divided by total number of shares outstanding. We obtain institutional ownership data from Thomason Financial and institutional investor classification data from Brian Bushee's website.[11]

He and Tian (2013) and Huang et al. (2017) provide an excellent discussion of the prior literature on the possible impact of analysts on earnings management. They stress that the presence of more analysts can have opposing effects on earning management: increase external performance pressure on firms to manage earnings while at the same time increase monitoring that could constrain earnings management. Empirically, they find that analysts exert too much pressure on managers to meet short-term earnings goals, which motivates firms to engage in upward earnings management.[12] We calculate the number of analysts following the firm (*NUMANA*) as the average number of analysts that make annual earnings-per-share forecasts in each month during the year. We obtain the analyst

[11] Bushee (1998) classifies institutional investors into transient, quasi-index and dedicated based on portfolio turnover and diversification by institutional investors. The classification data is available in the following website: http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html

[12] Prior research has also shown that analysts can play a monitoring role that reduces earnings management. For example, Yu (2008) finds that analyst coverage reduces accruals-based earnings management. As stressed earlier, it is possible that managers substitute real earnings management for accruals-based earnings management when accruals-earnings management is more constrained (Cohen et al., 2008). In the context of our study, if we find that more analyst coverage increases the positive association between asset redeployability and crash risk, the results will be consistent with an external performance pressure interpretation, similar to He and Tian (2013) and Huang et al. (2017).

following data from I/B/E/S.

The earnings response coefficient measures the extent of abnormal stock returns in response to the unexpected component of the firm's reported earnings. High values of the earnings response coefficient indicates a strong stock market reaction to firm earnings surprises. We specify the earnings response coefficient (*ERC*) as the regression coefficient by regressing market abnormal return against unexpected earnings for earnings announcements during the preceding three years. We follow Truong and Corrado (2014) in computing the market abnormal return during a three-day window around earnings announcements and measure unexpected earnings as actual earnings minus the median of analysts' forecasts, then scaled by stock price. We expect managers of firms whose stock prices are more sensitive to earnings, i.e., firms with higher earnings response coefficient, to face greater pressure to manage earnings in order to hide bad news.

In successive regressions, we interact asset redeployability with transient institutional ownership, analyst following, and the earnings response coefficient, and add the interaction terms to the analysis. The results are presented in Table 7. In Columns (1) and (2), we find that the coefficient on the interaction between asset redeployability and transient institutional ownership is positive and statistically significant in both the crash dummy and the negative skewness regressions (smaller *z*- or *t*-statistics 1.703). The evidence for the interactions involving analyst coverage and the earnings response coefficient appear in Columns (3) to (6). These results imply that the role that asset redeployability plays in stock price crash risk rises when there are more analysts following the firm and when the market reaction to unexpected earnings is high. Collectively, this evidence supports the narrative that managers with greater short-term performance pressure from the stock market are more likely to hide bad news using asset transactions, which results in a stronger effect of asset redeployability on crash risk.

[Insert Table 7 here]

6. Additional Analysis

6.1. The Effect of SOX

The Sarbanes-Oxley Act of 2002 (SOX) substantially increased the penalties for earnings manipulation, which led to a sharp decline in accruals earnings management after its enactment (Cohen et al., 2008; Graham et al., 2005). Hutton et al. (2009) documents an overall positive relation between discretionary accruals and stock price crash, although they also find that the relation disappears after the passage of SOX, suggesting that managers rely less heavily on hiding bad news through accruals earnings management in the post-SOX era. In this section, we examine whether the passage of SOX affects the relation between asset redeployability and stock price crash. Since managers can typically justify asset sales under the pretext that these transactions are undertaken in shareholders' best interests, they provide convenient cover for insiders to conceal bad news. Given that bad news hoarding activities are difficult to detect, managers may continue exploit asset sales after SOX. In fact, managers may resort to practicing even more real earnings management in this period since SOX constrains accruals-based earnings management.

To provide some insight on whether there is structural shift in the link between asset redeployability and stock price crash in the post-SOX era, we construct a post-SOX dummy (*POST_SOX*), which is equal to one for the post-SOX period (i.e., years after 2002), and zero otherwise. We interact asset redeployability with the post-SOX dummy and include the interaction term in the regression specification in equations (3) and (4). The results are presented in Table 8, which include that the coefficient on asset redeployability is positive and statistically significant (smaller *z*- or *t*-statistics 2.272), while the coefficient of the interaction term between asset redeployability and the post-SOX dummy has no perceptible impact. This suggests that the passage of SOX fails to deter managers from hiding bad news through asset transactions, likely reflecting that this legislation does not constrain real earnings management activities.

[Insert Table 8 here]

6.2. Asset Redeployability and Meet or Beat Analyst Forecasts

So far, we use stock price crash risk as an outcome measure to capture managerial bad news hoarding. Given that asset redeployability enables managers to hide bad news through asset transactions, we would expect asset redeployability to be associated with other measures of earnings manipulation. Accordingly, we provide additional evidence on managerial bad news hoarding by examining the impact of asset redeployability on the likelihood of beating analyst forecasts. Specifically, we define beat analyst forecasts (*BEAT_1C/BEAT_2C/ BEAT_3C*) as a dummy variable equal to one if the firm's actual earnings beat analyst forecast consensus by one cent/two cents/three cents, and zero otherwise.

We run the same regression as equation (3), with the three beat analyst forecast measures (instead of crash dummy) as the dependent variable, respectively. In Table 9, we report that the coefficient on asset redeployability is positive and statistically significant in all three regressions (smallest *z*-statistics 1.823). Overall, this evidence is consistent with our expectation that managers are able to exploit asset transactions to beat analyst forecasts when asset redeployability is high. This facilitates the withholding of bad news and subsequent stock price crash.

[Insert Table 9 here]

6.3. Asset Redeployability and Asset Sale Gain or Loss

Our hypothesis is that asset redeployability enables managers to manipulate earnings through asset transactions so that that they can hide bad news to inflate short-term stock prices. In this section, we directly analyze whether there is any relation between asset redeployability and firms' gain or loss in asset sales. We employ three measures of asset sale gains or losses. The first measure is the asset sale gain dummy (*AGAIN*), which is a dummy variable equal to one if the firm realizes gains in aggregate in assets sales during the fiscal year, and zero otherwise. The second measure is asset sale gain ratio (*R_AGAIN*), defined as the ratio of asset gains or losses over total assets. The third measure is abnormal asset sale gain ratio (*ABR_AGAIN*) derived after Gunny (2010) under this regression specification.

$$\frac{GainA_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 Q_t + \beta_3 \frac{INT_{i,t}}{AT_{i,t-1}} + \beta_4 \frac{ASales_{i,t}}{AT_{i,t-1}} + \beta_5 \frac{ISales_{i,t}}{AT_{i,t-1}} + \varepsilon_{i,t} \qquad (5)$$

where *GainA* is -1 times income from asset sales, *AT* is total assets, *INT* is internal funds (the sum of income before extraordinary expenses, depreciation and amortization, and R&D expenditure), *ASales* is long-lived asset sales, and *ISales* is long-lived investment sales. We estimate equation (5) by year and industry and take the residual as the abnormal asset sale gain ratio.

We run the same regression as equation (3), with the dependent variable specified as the asset sale gain dummy. We also run the same model as equation (4), with the dependent variable specified as the asset sale gain ratio and the abnormal asset sale gain ratio in successive regressions. The results from these estimations reported in Table 10. In all three estimations, the coefficient on asset redeployability is positive and statistically significant (smallest *z*- or *t*-statistics 2.004). This evidence implies that firms realize more asset sale gains than losses when asset redeployability is high. This helps empirically validate our argument that when asset redeployability is high, managers are in a better position to inflate earnings in an attempt to hide bad news through selling assets with book gains.

[Insert Table 10 here]

7. Conclusion

Prior research finds that firms' asset structure is associated with their financial stability (Miller and Orr, 1966; Williamson, 1986; Anand and Singh, 1997; Wagner, 2007). Asset redeployability, which captures the salability of corporate capital assets, has long been investigated about its role in firm's asset structure. In this paper, we extend extant evidence by analyzing whether asset redeployability shapes stock price crash risk. We find that firms with higher asset redeployability are more likely to have a future stock price crash. This evidence lends empirical support to the real earnings management channel in which managers dispose of corporate assets to manipulate earnings upward in order to hide bad news. Our results are robust to specifying alternative asset redeployability measures, estimating different model specifications, including additional control variables in the analysis, confronting endogeneity in an instrumental variables framework, and focusing on different sample periods.

In cross-sectional analysis, we find that the impact of asset redeployability on crash risk is stronger when CEOs are short-term oriented, e.g., when CEO equity incentives are high, CEOs are in the early or later years of their tenure, or CEOs are overconfident. Moreover, we find that the importance of asset redeployability to crash risk is concentrated in firms that are experiencing more pressure from external forces. Specifically, asset redeployability plays a larger role when: transient institutional investors hold large equity stakes in the firm, analyst coverage is relatively high, or firms have high earnings response coefficients.

We also conduct a series of additional analyses. We find that the positive association between asset redeployability and crash remains after SOX, potentially reflecting that this legislation does not focus on constraining real earnings management. Further, our evidence implies that asset redeployability is correlated with a higher likelihood of meeting or beating analyst targets. We also find that asset redeployability increases the likelihood of selling profitable assets. Collectively, our analysis suggests that asset redeployability increases the likelihood of a firm stock price crash given that firms exploit corporate asset sales to manipulate earnings when attempting to suppress negative information.

Our paper contributes to the literature on corporate asset sales and purchases. Against the backdrop of extensive prior research focusing on the positive consequences of asset redeployability, we provide evidence that asset redeployability has a dark side in the form of facilitating the withholding of bad news due to the historical cost nature of accounting for capital assets. Our analysis implies that investors can benefit from having a better understanding of the implications of financial reporting for capital assets. Specifically, in facing agency problems stemming from managerial incentives, investors need to protect their interests by closely monitoring firms against exploiting asset redeployability to conceal bad news that can lead to a stock price crash.

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APPENDIX. Variable Definitions

Variable	Definition
Crash dummy (*CRASH*)	Dummy variable equal to one for one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and zero otherwise.
Negative skewness (*NSKEW*)	Ratio of the third moment of firm-specific weekly returns over the standard deviation of firm-specific weekly returns raised to the third power, and then multiplied by -1.
Asset redeployability (*AR*)	Asset redeployability measure constructed following Kim and Kung (2017).
Return volatility (*SIGMA*)	Standard deviation of firm-specific weekly returns over the fiscal year.
Stock return (*RET*)	100 times the mean of firm-specific weekly returns over the fiscal year.
Stock turnover (*DTURN*)	Average monthly stock turnovers over the current fiscal year minus those over the previous fiscal year. Monthly stock turnover is calculated as the ratio of monthly trading volume over the number of shares outstanding.
Firm size (*SIZE*)	Log value of the market value of equity. Market value of equity is the product of stock price (PRCC_F) and the number of shares outstanding (CSHPRI).
Market-to-book (*MB*)	Ratio of the market value of equity over the book value of equity (CEQ). Market value of equity is the product of stock price (PRCC_F) and the number of shares outstanding (CSHPRI).
Leverage ratio (*LEV*)	Ratio of long-term debt (DLTT) over the book value of total assets (AT).
Return on assets (*ROA*)	Ratio of income before extraordinary items (IB) over book value of total assets (AT).
Abnormal accruals (*ABN_ACC*)	Absolute value of discretionary accruals, calculated using the modified Jones model of Dechow, Sloan, and Sweeney (1995).
Abnormal expenses (*ABN_EXP*)	Abnormal production costs minus abnormal discretionary expenses, calculated following Roychowdhury (2006) and Cohen and Zarowin (2010).
CEO equity incentives (*CEO_INCT*)	Ratio of the CEO's equity compensation pay-performance-sensitivity over the sum of equity compensation pay-performance-sensitivity, salary and bonus. CEO equity compensation pay-performance-sensitivity is the dollar change in the value of the CEO's stock and option holdings resulting from a 1% increase in the firm's stock price.
CEO tenure (*CEO_TNR*)	Dummy variable equal to one if the CEO is in the first three years and last year of tenure, and zero otherwise.
CEO overconfidence (*CEO_CONFI*)	Dummy variable equal to one for all years after a CEO holds options that are at least 67% in the money, and zero otherwise.
Transient institutional ownership (*TRAIO*)	Proportion of the firm's shares held by transient institutional investors. The classification of transient institutional investors follows Bushee (1998).
Analyst following (*NUMANA*)	Average number of analysts that make annual earnings-per-share forecasts in each month during the year.
Earnings response coefficient (*ERC*)	Earnings response coefficient, calculated as the regression coefficient by regressing market abnormal return against unexpected earnings for earnings announcements during the preceding three years.
Post-SOX dummy (*POST_SOX*)	Dummy variable equal to one for the post-SOX period (i.e., years after 2002), and zero for the pre-SOX period (i.e., years before 2002).

Beat analyst forecast dummy (*BEAT_1C/BEAT_2C/ BEAT_3C*)	Dummy variable equal to one if the firm's actual earnings beat analyst forecasts by one cent/two cents/three cents, and zero otherwise.
Asset sale gain dummy (*AGAIN*)	Dummy variable equal to one if asset gains/losses (SPPIV) is positive, and zero otherwise.
Asset sale gain ratio (*R_AGAIN*)	Ratio of asset gains/losses (SPPIV) over total assets (AT).
Abnormal asset sale gain ratio (*ABR_AGAIN*)	Abnormal asset sale gain ratio calculated following Gunny (2010).

Variable names in parentheses in the right column refer to the names of the data items in the merged Compustat/CRSP database.

TABLE 1. Summary Statistics

	Mean	S.D.	25%	Median	75%
CRASH	0.185	0.388	0.000	0.000	0.000
NSKEW	-0.057	0.812	-0.495	-0.077	0.339
AR	0.399	0.105	0.351	0.409	0.461
SIGMA	0.063	0.034	0.039	0.055	0.079
RET	-0.254	0.309	-0.309	-0.151	-0.073
DTURN	0.001	0.103	-0.023	0.000	0.023
SIZE	5.629	2.114	4.037	5.485	7.056
MB	3.336	5.514	1.196	1.961	3.387
LEV	0.160	0.168	0.004	0.116	0.265
ROA	0.006	0.199	-0.018	0.041	0.090
ABN_ACC	0.179	0.216	0.052	0.116	0.225
ABN_EXP	0.044	0.465	-0.150	0.071	0.298
Obs.			99,968		

The table presents the summary statistics of the variables in the analysis. Variable definitions are shown in the Appendix.

TABLE 2. Correlation Matrix

	CRASH	*NSKEW*	*AR*	*SIGMA*	*RET*	*DTURN*	*SIZE*	*MB*	*LEV*	*ROA*	*ABN_ACC*	*ABN_EXP*
CRASH	1.000											
NSKEW	0.607	1.000										
AR	0.013	0.017	1.000									
SIGMA	0.051	-0.015	0.003	1.000								
RET	-0.029	0.052	-0.012	-0.949	1.000							
DTURN	0.027	0.021	-0.014	0.107	-0.117	1.000						
SIZE	0.039	0.135	-0.040	-0.477	0.389	0.045	1.000					
MB	-0.006	-0.002	0.070	0.080	-0.092	0.057	0.123	1.000				
LEV	-0.013	-0.010	-0.110	-0.094	0.084	0.012	0.106	0.038	1.000			
ROA	0.002	0.024	0.024	-0.406	0.398	0.029	0.249	-0.129	-0.008	1.000		
ABN_ACC	-0.010	-0.011	0.004	0.151	-0.133	0.054	-0.052	0.071	0.071	-0.116	1.000	
ABN_EXP	0.013	0.013	0.021	-0.097	0.079	-0.049	0.051	-0.166	0.125	0.097	-0.034	1.000

The table presents the correlation matrix of the variables in the analysis. Variable definitions are shown in the Appendix.

TABLE 3. Asset Redeployability and Crash Risk: Main Results

Dependent Variable:	$CRASH_t$	$NSKEW_t$
	(1)	(2)
AR_{t-1}	**0.514**	**0.112**
	(2.729)****	**(2.715)******
$NSKEW_{t-1}$	0.070	0.031
	(4.576)***	(6.209)***
$SIGMA_{t-1}$	4.370	4.823
	(2.457)**	(13.017)***
RET_{t-1}	0.665	0.478
	(3.747)***	(13.870)***
$DTURN_{t-1}$	0.424	0.127
	(4.419)***	(3.613)***
$SIZE_{t-1}$	0.037	0.062
	(2.503)**	(17.862)***
MB_{t-1}	0.010	0.004
	(2.500)**	(4.135)***
LEV_{t-1}	-0.291	-0.135
	(-3.649)***	(-5.121)***
ROA_{t-1}	0.557	0.240
	(3.920)***	(5.228)***
ABN_ACC_{t-1}	0.142	0.062
	(3.568)***	(5.089)***
ABN_EXP_{t-1}	0.012	0.006
	(0.425)	(0.727)
Obs.	84,964	84,964
Pseudo/Adjusted R^2	0.021	0.051

The table presents regression results for the relation between asset redeployability and crash risk. Constant and year fixed effects are included in all the columns. The regression in column (1) is performed by Logit model and the regression in column (2) is performed by ordinary least squares (OLS). The *z*- or *t*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the Appendix.

TABLE 4. Asset Redeployability and Crash Risk: Robustness Checks

Panel A: Alternative asset redeployability measures		
(1) Redeployability measure incorporating correlation of outputs within industries		
Dependent variable:	*$CRASH_t$*	*$NSKEW_t$*
	(1)	(2)
AR_{t-1}	0.996	0.249
	(2.550)**	(2.751)***
(2) Equally weighted measure of redeployability		
Dependent variable:	*$CRASH_t$*	*$NSKEW_t$*
	(1)	(2)
AR_{t-1}	0.655	0.125
	(2.629)***	(2.347)**
Panel B: Alternative crash dummy measures		
(1) Define crash dummy by on 4 standard deviations below the mean		
Dependent variable:	*$CRASH_t$*	
	(1)	
AR_{t-1}	0.481	
	(2.876)***	
(2) Define crash dummy based on -15% cut-off		
Dependent variable:	*$CRASH_t$*	
	(1)	
AR_{t-1}	0.758	
	(3.014)***	
Panel C: Excluding financial crisis periods (1987, 2000-2002, and 2007-2008)		
Dependent variable:	*$CRASH_t$*	*$NCSKEW_t$*
	(1)	(2)
AR_{t-1}	0.575	0.115
	(2.973)***	(2.226)**

The table presents the regression results for various robustness checks. Control variables, constant and year fixed effects are included in all the columns. For the sake of brevity, the table does not report the coefficient of control variables. The regression in column (1) is performed by Logit model and the regression in column (2) is performed by ordinary least squares (OLS). The *z*- or *t*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the Appendix.

TABLE 5. Asset Redeployability and Crash Risk: Endogeneity Tests

Panel A: Additional control variables		
Dependent variable:	$CRASH_t$	$NCSKEW_t$
	(1)	(2)
AR_{t-1}	0.309	0.084
	(2.138)**	(2.067)**
Panel B: Random-effect panel regression		
Dependent variable:	$CRASH_t$	$NCSKEW_t$
	(1)	(2)
AR_{t-1}	0.512	0.090
	(3.425)***	(2.926)***

Panel C: Instrumental variable approach			
	First-Stage Regression	Second-Stage Regression	
Dependent Variable:	AR_{t-1}	$CRASH_t$	$NSKEW_t$
	(1)	(2)	(3)
Historical Industry AR	0.753		
	(10.474)***		
Instrumented AR_{t-1}		0.556	0.132
		(7.390)***	(3.069)***

The table presents results for endogeneity tests. Control variables, constant and year fixed effects are included in all the columns. For the sake of brevity, the table does not report the coefficient of control variables. In Panels A, the regression in column (1) is performed by Logit model and the regression in column (2) is performed by ordinary least squares (OLS). In Panels B, the regression in column (1) is performed by random-effect Logit model and the regression in column (2) is performed by random-effect panel regression. In Panel C, we use the Wooldridge (2002) method for crash dummy and two-stage least squares (2SLS) method for negative skewness. The *z*- or *t*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the Appendix.

TABLE 6. Asset Redeployability and Crash Risk: The Effect of Internal Performance Pressure

Dependent Variable:	$CRASH_t$ (1)	$NSKEW_t$ (2)	$CRASH_t$ (3)	$NSKEW_t$ (4)	$CRASH_t$ (5)	$NSKEW_t$ (6)
AR_{t-1}	0.351	-0.006	0.376	0.185	0.480	0.123
	(1.004)	(-0.061)	(0.947)	(1.720)*	(1.589)	(1.840)*
AR_{t-1}*CEO_INCT_{t-1}	**1.245**	**0.594**				
	(2.382)**	**(2.270)****				
CEO_INCT_{t-1}	-0.223	-0.170				
	(-0.682)	(-1.593)				
AR_{t-1}*CEO_TNR_{-1}			**0.580**	**0.009**		
			(2.164)**	**(1.279)**		
CEO_TNR_{-1}			0.271	0.006		
			(1.089)	(0.136)		
AR_{t-1}*CEO_CONFI_{t-1}					**0.630**	**0.100**
					(1.968)**	**(1.985)****
CEO_CONFI_{t-1}					-0.081	0.042
					(-0.621)	(1.041)
$NSKEW_{t-1}$	0.080	0.009	0.075	0.013	0.084	0.017
	(3.589)***	(1.031)	(3.555)***	(1.576)	(3.940)***	(2.077)**
$SIGMA_{t-1}$	6.891	5.933	8.063	5.846	7.393	5.420
	(2.615)***	(6.765)***	(3.290)***	(8.199)***	(3.035)***	(7.606)***
RET_{t-1}	0.827	0.592	0.998	0.605	0.878	0.550
	(2.724)***	(5.591)***	(3.442)***	(6.608)***	(3.156)***	(5.805)***
$DTURN_{t-1}$	0.251	0.051	0.184	0.046	0.226	0.059
	(1.221)	(0.829)	(0.931)	(0.821)	(1.162)	(1.072)
$SIZE_{t-1}$	-0.041	0.017	-0.030	0.024	-0.031	0.022
	(-2.023)**	(2.699)***	(-1.868)*	(4.673)***	(-2.086)**	(4.514)***

MB_{t-1}	0.009	0.002	0.011	0.003	0.010	0.002
	(2.200)**	(1.623)	(3.071)***	(2.421)**	(2.666)***	(1.810)*
LEV_{t-1}	-0.426	-0.157	-0.394	-0.152	-0.404	-0.152
	(-2.995)***	(-3.819)***	(-2.934)***	(-3.896)***	(-3.109)***	(-3.830)***
ROA_{t-1}	1.005	0.535	0.981	0.486	0.846	0.423
	(5.950)***	(10.740)***	(5.639)***	(11.035)***	(4.992)***	(9.315)***
ABN_ACC_{t-1}	0.239	0.057	0.229	0.083	0.157	0.051
	(2.896)***	(1.848)*	(3.010)***	(3.006)***	(1.985)**	(1.809)*
ABN_EXP_{t-1}	-0.059	0.009	-0.033	0.006	0.062	0.044
	(-1.315)	(0.650)	(-0.868)	(0.471)	(1.498)	(1.748)*
Obs.	19,350	19,350	23,660	23,660	23,784	23,784
Pseudo/Adjusted R^2	0.015	0.025	0.016	0.025	0.014	0.028

The table presents regression results for the effect of internal performance pressure on the relation between asset redeployability and crash risk. Constant and year fixed effects are included in all the columns. The regression in columns (1), (3), and (5) is performed by Logit model and the regression in columns (2), (4), and (6) is performed by ordinary least squares (OLS). The *z*- or *t*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the Appendix.

TABLE 7. Asset Redeployability and Crash Risk: The Effect of External Performance Pressure

Dependent Variable:	*CRASH*$_t$ (1)	*NSKEW*$_t$ (2)	*CRASH*$_t$ (3)	*NSKEW*$_t$ (4)	*CRASH*$_t$ (5)	*NSKEW*$_t$ (6)
AR_{t-1}	0.365	0.055	0.247	0.054	0.743	0.105
	(1.962)**	(1.279)	(1.793)*	(1.854)*	(2.303)**	(2.242)**
AR_{t-1}*$TRAIO_{t-1}$	**1.501**	**0.694**				
	(1.703)*	**(2.158)****				
$TRAIO_{t-1}$	0.982	0.362				
	(2.036)**	(2.512)**				
AR_{t-1}*$NUMANA_{t-1}$			**0.217**	**0.053**		
			(2.243)**	**(1.846)***		
$NUMANA_{t-1}$			0.002	0.012		
			(0.030)	(0.979)		
AR_{t-1}*ERC_{-1}					**0.010**	**0.002**
					(2.753)***	**(1.824)***
ERC_{-1}					-0.015	-0.001
					(-1.399)	(-0.448)
$NSKEW_{t-1}$	0.061	0.027	0.062	0.028	0.054	0.015
	(3.940)***	(5.238)***	(4.046)***	(5.474)***	(2.690)***	(2.168)**
$SIGMA_{t-1}$	1.862	4.019	3.792	4.617	8.357	5.988
	(1.154)	(11.698)***	(2.238)**	(12.900)***	(3.817)***	(11.052)***
RET_{t-1}	0.418	0.402	0.611	0.460	0.898	0.580
	(2.595)***	(12.516)***	(3.608)***	(13.809)***	(3.424)***	(10.525)***
$DTURN_{t-1}$	0.321	0.091	0.445	0.135	0.413	0.135
	(3.368)***	(2.589)***	(4.632)***	(3.890)***	(2.617)***	(2.846)***
$SIZE_{t-1}$	0.014	0.054	0.009	0.052	0.015	0.045
	(1.095)	(19.761)***	(0.701)	(15.823)***	(1.090)	(11.232)***

MB_{t-1}	0.010	0.004	0.011	0.005	0.013	0.006
	(3.020)***	(5.311)***	(3.060)***	(4.933)***	(3.337)***	(4.461)***
LEV_{t-1}	-0.286	-0.132	-0.292	-0.135	-0.261	-0.165
	(-3.788)***	(-5.212)***	(-3.804)***	(-5.384)***	(-2.607)***	(-5.113)***
ROA_{t-1}	0.500	0.218	0.561	0.239	0.823	0.392
	(3.780)***	(4.940)***	(3.995)***	(5.265)***	(4.782)***	(6.350)***
ABN_ACC_{t-1}	0.145	0.063	0.163	0.070	0.124	0.051
	(3.685)***	(5.226)***	(4.077)***	(5.745)***	(1.603)	(1.808)*
ABN_EXP_{t-1}	0.024	0.010	0.020	0.009	0.044	0.035
	(0.833)	(1.314)	(0.697)	(1.116)	(1.174)	(1.865)*
Obs.	84,964	84,964	84,964	84,964	35,537	35,537
Pseudo/Adjusted R^2	0.024	0.056	0.021	0.053	0.018	0.036

The table presents regression results for the effect of external performance pressure on the relation between asset redeployability and crash risk. Constant and year fixed effects are included in all the columns. The regression in columns (1), (3), and (5) is performed by Logit model and the regression in columns (2), (4), and (6) is performed by ordinary least squares (OLS). The *z*- or *t*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the Appendix.

TABLE 8. Asset Redeployability and Crash Risk: The Effect of SOX

Dependent Variable:	$CRASH_t$	$NSKEW_t$
	(1)	(2)
AR_{t-1}	0.501	0.092
	(2.341)**	(2.272)**
AR_{t-1}*POST_SOX	**0.056**	**0.044**
	(0.295)	**(0.753)**
POST_SOX	0.322	0.167
	(3.009)***	(2.873)***
$NSKEW_{t-1}$	0.071	0.031
	(4.563)***	(6.212)***
$SIGMA_{t-1}$	4.061	4.829
	(2.332)**	(13.035)***
RET_{t-1}	0.647	0.479
	(3.760)***	(13.875)***
$DTURN_{t-1}$	0.387	0.126
	(4.049)***	(3.613)***
$SIZE_{t-1}$	0.033	0.062
	(2.216)**	(17.892)***
MB_{t-1}	0.010	0.004
	(2.580)***	(4.069)***
LEV_{t-1}	-0.302	-0.135
	(-3.760)***	(-5.090)***
ROA_{t-1}	0.539	0.240
	(3.815)***	(5.231)***
ABN_ACC_{t-1}	0.124	0.063
	(3.125)***	(5.123)***
ABN_EXP_{t-1}	0.008	0.006
	(0.289)	(0.716)
Obs.	81,975	81,975
Pseudo/Adjusted R^2	0.302	0.051

The table presents regression results for the effect of SOX on the relation between asset redeployability and crash risk. Constant and year fixed effects are included in all the columns. The regression in column (1) is performed by Logit model and the regression in column (2) is performed by ordinary least squares (OLS). The *z*- or *t*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the Appendix.

TABLE 9. Asset Redeployability and Meet/Beat Analyst Forecasts

Dependent Variable:	$BEAT\_1C_t$	$BEAT\_2C_t$	$BEAT\_3C_t$
	(1)	(2)	(3)
$\boldsymbol{AR_{t-1}}$	**0.959**	**0.937**	**0.817**
	(2.274)**	**(2.200)****	**(1.823)***
$NSKEW_{t-1}$	-0.018	-0.028	-0.034
	(-0.844)	(-1.506)	(-1.860)*
$SIGMA_{t-1}$	4.460	3.373	2.744
	(1.946)*	(1.824)*	(1.576)
RET_{t-1}	0.745	0.572	0.430
	(2.968)***	(3.146)***	(2.387)**
$DTURN_{t-1}$	-0.314	-0.395	-0.459
	(-2.328)**	(-3.689)***	(-4.487)***
$SIZE_{t-1}$	-0.066	-0.020	-0.004
	(-4.911)***	(-1.706)*	(-0.286)
MB_{t-1}	0.023	0.023	0.025
	(5.813)***	(5.759)***	(5.688)***
LEV_{t-1}	-0.679	-0.901	-0.967
	(-5.660)***	(-8.054)***	(-8.668)***
ROA_{t-1}	1.338	1.556	1.767
	(10.101)***	(10.261)***	(10.801)***
ABN_ACC_{t-1}	-0.067	-0.050	-0.052
	(-0.880)	(-0.750)	(-0.815)
ABN_EXP_{t-1}	0.009	-0.043	-0.042
	(0.180)	(-0.926)	(-0.938)
Obs.	41,920	41,920	41,920
Pseudo R^2	0.029	0.039	0.044

The table presents regression results for the relation between asset redeployability and meet/beat analyst forecasts. Constant and year fixed effects are included in all the columns. The regression is performed by Logit model. The *z*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the Appendix.

TABLE 10. Asset Redeployability and Asset Sale Gain/Loss

Dependent Variable:	$AGAIN_t$	R_AGAIN_t	ABR_AGAIN_t
	(1)	(2)	(3)
$\boldsymbol{AR_{t-1}}$	**0.962**	**0.006**	**0.002**
	(2.004)**	**(2.807)*****	**(3.380)*****
$NSKEW_{t-1}$	0.044	0.000	0.000
	(3.182)***	(2.721)***	(0.627)
$SIGMA_{t-1}$	15.661	0.019	0.024
	(8.036)***	(1.717)*	(2.948)***
RET_{t-1}	1.224	0.003	0.002
	(6.620)***	(2.830)***	(2.947)***
$DTURN_{t-1}$	-0.451	-0.000	-0.002
	(-5.009)***	(-0.489)	(-2.092)**
$SIZE_{t-1}$	-0.064	-0.000	-0.000
	(-4.169)***	(-0.014)	(-1.479)
MB_{t-1}	0.015	-0.000	0.000
	(4.408)***	(-1.041)	(1.041)
LEV_{t-1}	-0.834	-0.001	-0.000
	(-5.825)***	(-1.211)	(-0.525)
ROA_{t-1}	0.158	0.003	0.002
	(1.145)	(2.642)***	(2.426)**
ABN_ACC_{t-1}	-0.022	-0.000	-0.000
	(-0.269)	(-0.821)	(-0.320)
ABN_EXP_{t-1}	-0.254	-0.001	-0.000
	(-5.570)***	(-3.000)***	(-2.523)**
Obs.	41,684	79,197	59,867
Pseudo/Adjusted R^2	0.031	0.041	0.054

The table presents regression results for the relation between asset redeployability and assets sale gain/loss. Constant and year fixed effects are included in all the columns. The regression in column (1) is performed by Logit model and the regression in columns (2) and (3) is performed by ordinary least squares (OLS). The *z*- or *t*-statistics (in parentheses) are computed using standard errors robust to heteroskedasticity and clustering at both the firm and industry levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are shown in the Appendix.