The Impact of Conservatism and Supply Chain Finance on Bad Debt Expense ☆

Sudipta Basu
Fox School of Business
Temple University
sudipta.basu@temple.edu

Tom Canace
School of Business
Wake Forest University
canacetg@wfu.edu

Mark Cecchini
Darla Moore School of Business
University of South Carolina
cecchini@moore.sc.edu

Yi Liang
McIntire School of Commerce
University of Virginia
syx2zr@virginia.edu

September 2022

☆ We thank Yi-Chun Chen (discussant), Scott Jackson, Jay Junghun Lee (discussant), Xiaotao (Kelvin) Liu, Vivek Raval (discussant), Wei Wang, Charlie Wasley, and workshop participants at the 2022 American Accounting Association Annual Meeting, 2022 Canadian Academic Accounting Association Annual Conference, 2022 Hawaii Accounting Research Conference, Temple University (brownbag and accounting workshops), University of Rochester, Villanova University and Wake Forest University for helpful comments and suggestions. We thank Rob Kortman and Danny Siemes (PwC) for sharing their insights about supply chain finance. We also thank Carter Van Winkle and Zhongnan Xiang for excellent research assistance.

The Impact of Conservatism and Supply Chain Finance on Bad Debt Expense

ABSTRACT

Standard accrual models assume a parsimonious, linear relation between accruals and changes in sales but ignore the accounting methods and real transactions that generate accruals. Hence, legitimate transactions are often modeled as earnings management. We focus on a specific accrual, bad debt expense (BDE), and develop accounting-based models. We find that accounting-based models that incorporate conservatism have much better explanatory power. This is because, due to conservatism, receivables can be written off but are rarely written up, creating an asymmetry in BDE that linear models cannot capture. We then investigate the effect of real transactions on BDE by examining supply chain finance, which reduces the risk of receivables. We predict and find that supply chain finance decreases the level and asymmetry of BDE, which would likely be misclassified as earnings management by standard models. Our study highlights the importance of modeling individual accruals using accounting methods and incorporating real transactions.

Keywords: bad debt expense; supply chain finance; conservatism; write-offs; receivables

1. Introduction

Standard accrual models such as the Jones (1991) model and its modifications (e.g., Dechow et al., 1995) often model accruals as a linear function of changes in sales and other proxies for economic activities. A linear specification, however, ignores the accounting methods and real transactions that affect the accrual-generating process (Fields et al., 2001). Thus, many legitimate transactions and accounting treatments are often classified as earnings management (Dechow and Skinner, 2000). In this study, we focus on modeling a specific component of accruals, bad debt expense (BDE), which allows us to develop better models by linking the component to its accounting methods and real transactions (Bernard and Skinner, 1996). We find that accounting-based models that incorporate conservatism have much better explanatory power than linear models because they capture the asymmetry that arises from conservatism, which is prevalent in accounting methods (Basu, 1997; Barker and McGeachin, 2015). We also show that supply chain finance (SCF),[1] a real transaction that reduces the risk of receivables, decreases the level and conservatism of BDE. Thus, if not modeled properly, both conservatism and SCF would be misclassified as earnings management.

We examine BDE because its accounting methods (i.e., a balance sheet approach based on the percentage of receivables and an income statement approach based on the percentage of sales) are explicitly specified, which allows us to develop empirical models accordingly. Due to conservatism, firms write off accounts receivable when customers cannot pay.[2] However, subsequent recoveries are not permitted unless payment is received (Jackson and Liu, 2010; McNichols and Wilson, 1988), leading to an asymmetry in BDE that is not reflected in linear

[1] Broadly speaking, SCF includes reverse factoring as well as other instruments such as dynamic discounting, purchase-order financing, collective invoices, etc. (Hofmann et al., 2021). Among them, reverse factoring is perhaps most widely used, so SCF and reverse factoring are often used interchangeably (e.g., PwC, 2019).

[2] Unless otherwise noted, we use gross accounts receivable, accounts receivable, and receivables interchangeably.

models.[3] BDE is also one of the very few instances where outsiders can observe an accrual on the income statement and its companion on the balance sheet, accounts receivable.[4] Thus, we can compare BDE with accounts receivable and write-offs to directly assess the accrual-generating process against real activities and events.[5] The potential implication of our study, however, is not restricted to BDE because managers likely treat BDE and other accruals in similar ways, and our findings can be broadly reflective of a firm's overall accrual decisions.

Following Jackson and Liu (2010), we collect BDE and write-offs data from Schedule II of Form 10-K and construct a sample from 1988 to 2017.[6] Figure 1 plots the means of BDE and write-offs (both scaled by average total assets) for each sample year.[7] We find that BDE and write-offs are quite close to each other. This observation suggests that write-offs are an important determinant of BDE, and the balance sheet approach (which directly incorporates write-offs into BDE) is widely used, consistent with the prior literature (McNichols and Wilson, 1988).

We start our empirical analysis by imposing no parametric assumptions and plotting BDE against change in adjusted sales, the explanatory variable from the modified Jones model (Dechow et al., 1995). We find a surprising V-shaped relation between them. That is, while linear models often find that accruals increase with change in adjusted sales, we find that this pattern holds only for positive changes in adjusted sales. When adjusted sales decline, BDE decreases with changes in adjusted sales. This finding suggests that linear models for BDE are

---

[3] In contrast, recoveries are possible under IFRS (IFRS 9), leading to weaker or even no asymmetry. However, because we examine a U.S. sample, we expect the asymmetry to exist.
[4] Other items such as disclosures on restructuring charges are mandated only in more recent years. The underlying restructuring activities may also differ substantially across firms.
[5] Following the prior literature (e.g., Jackson and Liu, 2010; McNichols and Wilson, 1988), we view write-offs as based on real events (i.e., customers' inability to pay), and hence, as unmanageable or significantly less manageable than BDE and allowances for bad debt.
[6] We further collect write-off data for 2018 and use it as a control variable in our empirical analysis.
[7] Figure 1 also plots the expected write-offs (EWO) and unexpected write-offs (UWO), which will be discussed in Section 5.

misspecified but is consistent with conservatism which often induces an asymmetry (Basu, 1997). For example, when bad events happen and adjusted sales decline, firms make more conservative adjustments (e.g., write-offs), and hence, report more BDE.

Next, we develop and estimate models based on accounting methods and compare their explanatory power with that of the modified Jones model. Our results show that the explanatory power of the income statement and modified Jones models is low. Results (untabulated) are similar for the Jones (1991) model. The explanatory power of the balance sheet model is substantially better, and the improvement stems from the inclusion of write-offs, a conservative adjustment that helps explain the V-shaped asymmetry. When we add write-offs to the other models, they become comparable to the balance sheet model. Another way to empirically account for the asymmetry is by using a piece-wise linear structure, e.g., including the interaction of change in adjusted sales and an indicator for adjusted sales decline (see Basu, 1995; Byzalov and Basu, 2016). We find that the piece-wise linear structure further improves the explanatory power because firms can implement conservatism in ways other than write-offs.

We then decompose write-offs into an expected component and an unexpected component by regressing write-offs on their two sources, prior period receivables and current period sales revenue, and then computing the two components as the expected value and residual, respectively. We predict that the incremental explanatory power of write-offs mainly comes from the unexpected component because it captures the conservative adjustments resulting from firm-specific bad news and/or market-wide adverse shocks such as recessions. For example, in Figure 1, both BDE and write-offs reach their local maxima during recessions, and this variation is mostly reflected in the unexpected component. Again, we find evidence supporting our prediction.

Further, we examine the effect of real transactions on BDE by exploiting the emergence and adoption of SCF, which gained popularity after the 2007-08 financial crisis. SCF is being widely adopted by firms, with an estimated amount financed of $1.5 trillion globally in 2020, according to the 2020 McKinsey Global Payments report. The growth of SCF and historical lack of transparency has caused the FASB to take action, requiring companies to disclose the size of their SCF programs (FASB Exposure Draft 405-50) starting in 2023.

The benefits of SCF accrue to three parties: buyers, suppliers, and banks. Buyers improve their cash conversion cycles through prolonged payments. Suppliers (the focus of our study) receive payment for receivables sooner. Banks benefit by collecting interest revenue on the amount financed. Because SCF transfers the risk of receivables from suppliers to banks (Chuk et al., 2021), it allows suppliers to estimate less BDE, reducing their conservatism. This prediction is consistent with the decreases in both the level and volatility of BDE after the financial crisis (see Figure 1). To test our prediction, we classify industries into two groups, high SCF and low SCF. We find that high SCF industries had greater decreases in both the level and asymmetry in BDE. We consider a second, firm-level measure of SCF adoption by accounting for the change in days sales outstanding (as SCF adopters are more likely to enjoy a large decrease). We find consistent results. These changes in BDE are likely due to legitimate accounting judgments, but the modified Jones model would classify them as earnings management.

Finally, to establish the importance of accounting-based models and modeling real transactions, we conduct simulations following Dechow et al. (2012). We find that models that incorporate write-offs and the piece-wise linear structure have much better Type I and Type II errors for detecting BDE-related earnings management (hereafter BDE management). Splitting the full sample into subsamples based on SCF adoption can also help avoid mistakenly classifying non-BDE management firms as BDE-management firms (i.e., Type I error).

Our findings highlight the importance of adjusting accrual models to reflect accounting methods and real transactions. Because accounting methods are often conservative, it is important to incorporate adjustments such as write-offs, especially during economic downturns when such adjustments are larger. It would also be beneficial to analyze narrower settings and focus on particular accrual components because it allows researchers to develop empirical models based on accounting methods and fully examine the accrual-generating processes. Furthermore, consistent with Owens et al. (2017), who suggest that idiosyncratic shocks affect firms' accrual-generating process, our SCF analysis demonstrates that firms' accruals are affected by real business activities, which should be incorporated to better model accruals. Finally, our study also suggests that the residuals of linear models contain conservative adjustments that are largely nondiscretionary (cf. Lawrence et al., 2013) and, if these residuals are used as a proxy for earnings management, may lead to invalid findings.

2. The institutional background of bad debt expense

2.1 Accounting methods for bad debt expense

2.1.1 Balance sheet and income statement approaches

To estimate BDE, managers can use either a balance sheet approach or an income statement approach (McNichols and Wilson 1988; Jackson and Liu 2010).[8] The balance sheet approach, which is also known as the allowance method, derives BDE from the change in allowance for doubtful accounts (*ALLOW*). In particular, the balance sheet approach first estimates the allowance as a percentage (φ) of gross accounts receivable (*AR*), and BDE results

[8] We do not examine the third approach, direct write-off method, because it is used for tax reporting purposes only.

from a change in allowance from the prior period as follows:[9]

$$BDE_t = ALLOW_t - ALLOW_{t-1} = \varphi \Delta AR_t \quad (1)$$

where φ is often determined using information from various sources such as the aging of receivables, macroeconomic factors, and industry-specific shocks (McNichols and Wilson, 1988; Frankel et al., 2020).

Equation (1) is similar to the standard accrual models that view accruals as a result of changes in working capital accounts without conservative adjustments (e.g., Jones, 1991; Dechow et al., 1995). However, accounting rules require firms to remove from the books a specific receivable if it is found to be uncollectible, which leads to a write-off (*WO*) and reduces the allowance as well. Hence, to correctly derive BDE under the balance sheet approach, write-offs must be added back to reflect their impact on the change in allowance, and the "complete" BDE equation based on the balance sheet approach is as follows:

$$BDE_t = \varphi \Delta AR_t + WO_t \quad (2)$$

In contrast, the income statement approach estimates BDE as a percentage (δ) of sales revenue (*SALE*), which can be represented as follows:

$$BDE_t = \delta SALE_t \quad (3)$$

2.1.2 The role of write-offs

A key difference between the balance sheet approach (equation (2)) and the income statement approach (equation (3)) is the sequence of calculation. The balance sheet approach requires managers to first estimate the allowance and identify write-offs, and BDE is then calculated as a "residual" that reconciles the relation between current allowance, prior-year allowance, and write-offs (Dichev, 2008). The income statement approach, however, requires

[9] Equation (1) assumes φ to be a constant. In Section 3, we relax this assumption and specifically consider how conservatism affects φ.

managers to apply the matching principle, assuming that BDE arises when sales are made, and hence, estimate BDE before determining allowance (Dichev and Tang, 2008).

This difference also causes write-offs to play differential roles in BDE estimation. Under the balance sheet approach, although write-offs do not increase BDE directly, they can increase BDE *indirectly* through their effect on the allowance.[10] In contrast, there is no clear link between write-offs and BDE under the income statement approach as long as the allowance is sufficiently large,[11] which is likely the case in practice because allowances are often much greater than future write-offs, especially after the early 1990s (Jackson and Liu, 2010). The differential roles of write-offs are also reflected in equations (2) and (3), where *WO* only appears in the former.

Hence, under the balance sheet approach, write-offs are an important component to incorporate when modeling BDE. However, the effect of write-offs is unlikely to be captured by traditional linear accruals models because write-offs are adjustments made by firms that reflect conservatism, and hence, often exhibit an asymmetry (Byzalov and Basu, 2016). In particular, while firms often write off receivables when customers are unable to pay, the standard for a write-up (i.e., recovery) is much higher. ASC 310-10-35-41 allows firms to recognize a recovery only after cash is received. Therefore, the "net" write-offs incorporate bad news faster than good news, reflecting conditional conservatism of financial reporting (Basu, 1997).

2.1.3 The use of two estimation approaches

Prior literature suggests that the balance sheet approach is more widely adopted by credit managers in financial reporting, although they often start with the income statement approach (McNichols and Wilson, 1988). The advantage of (starting with) the income statement approach

[10] Writing off uncollectible accounts results in a debit to the allowance and a credit to accounts receivable. Hence, BDE is not directly involved in the writoff journal entry.
[11] Accounting rules require that, regardless of the estimation approach, managers must ensure that allowance is adequate (Revsine et al., 2017).

is that it can facilitate business planning and forecasts during the fiscal period (Basu and Waymire, 2010; Lee, 2014). Because most firms are created to earn revenue while incurring expenses, the income statement approach is perhaps the more intuitive approach to use when managers prepare budgets (Dichev, 2008). Firms often use autoregressive integrated moving average time-series models to forecast future sales and then, based on the forecasted future sales, predict future income statement items such as BDE (Badertscher et al., 2012; Chase, 2013).

By the end of the fiscal period, however, firms switch to the balance sheet approach to ensure that receivables represent the expected future collection (McNichols and Wilson, 1988). Three reasons can justify this choice. First, the firms' creditors likely prefer the balance sheet approach because it focuses on measuring assets and liabilities, and hence, can provide a more precise estimate of firms' net value, which is particularly relevant to creditors when liquidation occurs (Holthausen and Watts, 2001). Also, creditors may prefer the balance sheet approach because it features write-offs, a conservative adjustment. Prior studies suggest that creditors often demand conservatism because it increases covenant violation probability, and hence, gives creditors more opportunities to take control of the firm (e.g., Watts, 2003; Zhang, 2008).[12]

Second, auditor scrutiny also incentivizes the adoption of the balance sheet approach. Auditors are required to evaluate the adequacy of the allowance based on the aged trial balance (Arens et al., 2020). Thus, instead of attesting to BDE directly, auditors often first verify receivables, the allowance, and write-offs, and then check BDE simply as the residual similar to the balance sheet approach.

Third, FASB also seems to promote the balance sheet approach (O'Brien, 2009). In its

[12] Demerjian (2011) finds that creditors used fewer balance sheet-based covenants in recent years because the FASB's balance sheet approach features estimations that are not conservative (e.g., fair value accounting). For bad debt expense, however as discussed above, the balance sheet approach is likely more conservative than the income statement approach.

2010 conceptual framework, FASB emphasized that firms should first measure their economic resources and claims to them (i.e., assets and liabilities), and then calculate performance as the change in such resources and claims (Benston et al., 2007). Also, the FASB and IASB removed the matching principle from their joint 2010 conceptual framework, reducing the legitimacy of an income statement approach that follows the matching principle.

2.2 Bad debt expense and the modified Jones model

The Jones (1991) model and its modifications (e.g., Dechow et al., 1995) are widely used to model accruals. Jones (1991) argues that accruals arise when there are changes in firms' economic circumstances which drive the changes in working capital accounts (Kaplan, 1985; Kothari et al., 2005). Thus, the Jones model indirectly takes a balance sheet perspective (without incorporating conservative adjustments such as write-offs) and uses sales as a proxy for economic circumstances. In this study, we focus on Dechow et al.'s (1995) modified Jones model although we find consistent results if we estimate the Jones model. When applied to BDE, a modified Jones model can be specified as follows:

$$BDE_{it} = \beta_0 + \beta_1 \Delta ADJ\_SALE_{it} + \epsilon_{it} \tag{4}$$

where *ΔADJ_SALE* stands for change in adjusted sales revenue, defined as the change in sales revenue minus the change in accounts receivable. We drop property, plant and equipment from the original modified Jones model because it is included to capture depreciation, which is irrelevant to BDE.[13]

Model (4) is different from the income statement approach (equation (3)) because it assumes BDE is a function of the change in sales, but not sales. It is also different from the

[13] Sometimes the Jones and modified Jones models also include the inverse of beginning total assets as a control variable. However, it is often dropped in recent applications (e.g., McNichols, 2002; Basu and Byzalov, 2016). We also elect to drop it so that the modified Jones model is more comparable to the other two models.

balance sheet approach (equation (2)) in two aspects. First, the balance sheet approach directly relates BDE to gross accounts receivable, but the Jones model uses sales as a proxy for receivables. This proxy will work well if and only if the relation between receivables and sales is largely constant. Second, as discussed above, write-offs are omitted from the Jones model.

Due to these differences, although the Jones model takes a balance sheet perspective, it is unlikely to fit the real BDE data very well. However, if write-offs are added to the model, we expect that the Jones model would work reasonably well to the extent that change in sales is a reliable proxy for change in receivables.

2.3 Supply chain finance and bad debt expense

SCF, most commonly reverse factoring, involves a supplier, a customer, a financial institution (e.g., a bank) as well as an SCF platform that handles the SCF arrangements. In a typical SCF arrangement, the financial institution arranges with the customer to obtain approval of the supplier invoices. Once the customer approves the invoices and commits to paying them at maturity, cash is then immediately released to the supplier at a discounted rate (the discount is irevenue for the financial institution assuming the risk). Thus, SCF provides the supplier with financing facilities by leveraging the customer's credit rating (Chuk et al., 2021). While reverse factoring is the most common supply chain solution, dynamic discounting and purchase order financing are other possible SCF arrangements. For our research, the most relevant SCF solution is reverse factoring due to the effect it may have on supplier receivables.

SCF benefits both buyers and suppliers. Buyers want to pay as late as possible, and sellers want to receive payment as early as possible. SCF tries to bridge these competing interests (Sommer and O'Kelly, 2017). Banks are the primary mediators in SCF but institutions such as investment funds and digital platforms also participate. The components of the cash conversion cycle (CCC) are the Days sales outstanding (DSO), Days payables outstanding (DPO) and Days inventory outstanding (DIO). The functional relationship is CCC = DIO + DSO – DPO. Assuming DIO is held constant (as it is related to firm inventory policies which are beyond the scope of this paper), the function boils down to CCC = DSO – DPO. Firms benefit from CCC being 0 or negative. A 0 value suggests that firms are receiving payment from customers for product sales at the same time as they are paying their suppliers for the product inventory. This allows companies to effectively finance their day-to-day operations with revenue, lowering their overall financing costs. Here is an example to illustrate how SCF works for both sides of a transaction. Buyer A purchases from Seller B with net 60 terms. Adopting SCF can help Buyer A achieve a 0 or negative CCC by allowing Buyer A to raise DPO to 90 days without hurting Seller B. Seller B can still achieve 0 or negative CCC by lowering the DSO by receiving payment in 30 days from the bank. Assuming the finance cost is low enough, this is a win/win/win because the bank earns interest revenue by facilitating this transaction.

Consumer goods and manufacturing are sectors with high supply chain finance because these industries have high transaction volumes. The SCF market is still dominated by larger companies, but smaller companies are now using it too. The 2020 McKinsey Global Payments Report estimates that SCF is involved in $1.5 trillion of business transactions globally. This number is likely to grow as there are an estimated $17 trillion of invoices and receipts annually worldwide. According to the World Economic Forum (2019), the SCF market will be $2.5 trillion by 2025. Some barriers to the adoption of SCF are lack of transaction volume, cost of adoption, and resistance to information technology (PwC, 2018/2019). As the market share of SCF increases, it becomes increasingly important to consider its accounting effects on suppliers, especially for their BDE and the allowance for doubtful accounts.

FASB recently approved a new SCF disclosure rule, to take effect in early 2023 (FASB Exposure Draft 405-50). The new rule will require firms to disclose the outstanding balance of their SCF programs quarterly, along with year-over-year comparisons. This rule addresses a concern that SCF is causing hidden debt, which leads to hidden risks of insolvency, neither of which is being properly communicated to investors and creditors.[14] Rating agencies worry this hidden debt can be recalled quickly under financial pressure. Until now, there have been no policies or standard contracts in SCF, making it difficult to model the risks. Companies argue this new disclosure will be cumbersome, costly and unnecessary. Investors and regulators worry this will not be enough. According to Wang et al. (2020), Capital Pressure and Order fulfillment cycle are drivers of SCF adoption. According to Chuk et al. (2021), adoption of SCF is more likely for buyers that use more trade credit, have a lower cost of debt, are larger, older, have lower return volatility and depend more on external financing. Chuk et al. (2021) find that buyers that adopt SCF pay later (a buyer goal), have a lower likelihood of financial distress, and a higher ROA. The economic incentives for the buyer to adopt are unambiguous. The benefits of buyer adoption of SCF spillover to the supplier in the form of lower risk of nonpayment and a shorter order to cash cycle (lower DSO). Thus, as suppliers adopt SCF, they may recognize less BDE than before. Also, because SCF has been increasingly used since the financial crisis in 2008 (Hofmann et al. 2021), we expect the decrease in BDE to be concentrated in the period after the financial crisis. We also expect that lower collection risk will lower conservatism in BDE.[15]

[14] British builder Carillon went bankrupt suddenly in 2018 with over $8B in SCF from its SCF program. Greensill Capital, on the financing side of SCF, collapsed with $9.3B of unpaid SCF. Political intervention into the Greensill bankruptcy caused a political scandal in the UK, prompting an outcry call for greater transparency in SCF arrangements.

[15] Some suppliers may have only low-risk buyers adopt SCF while almost all high-risk buyers do not adopt (leaving only high-risk receivables on the books), leading to increased conservatism. If SCF adoption is industry-specific, then we expect that this situation would be uncommon.

3. Empirical design

3.1 Baseline models

Our empirical balance sheet model is based on equation (2). In the regression model below, we estimate the average percentage of gross accounts receivable (β_1) used by firms to determine the allowance. We also estimate the coefficient on write-offs (β_2) instead of setting it to be one, consistent with prior studies (e.g., McNichols and Wilson, 1988).

$$BDE_{it} = \beta_1 \Delta AR_{it} + \beta_2 WO_{it} + \omega_i + \epsilon_{it} \quad (5)$$

where ω represents firm fixed effects, which control for firm-level time-invariant factors that affect BDE, and ε is the regression error term. We scale all variables by average total assets for our empirical analysis. We cluster standard errors by firm.[16]

Our empirical income statement model is based on equation (3). In the regression below, we estimate the average percentage of sales (γ) used by firms to compute BDE as follows:

$$BDE_{it} = \gamma SALE_{it} + \omega_i + \epsilon_{it} \quad (6)$$

Finally, we estimate the modified Jones model in equation (4). To make it comparable to the previous two models, we replace the intercept with firm fixed effects.

To compare the models, we measure their explanatory power using adjusted within R^2, which excludes the variation in data captured by firm fixed effects. Although firm fixed effects can improve the overall R^2, they do not reflect how well the explanatory variables that we are interested in such as write-offs explain BDE. Thus, it is helpful to exclude them when assessing incremental explanatory power.

3.2 Piece-wise linear models

As discussed, besides write-offs, managers can implement conservatism by adjusting the

[16] In Appendix B, we review the BDE models estimated in the prior literature and compare them with our models.

percentages that they apply to estimate BDE. For example, managers may increase the percentages when the collectability of receivables worsens but keep the percentages unchanged when the situation improves, causing an asymmetric relation between BDE and receivables (Basu et al. 2020). To capture this pattern, we follow prior research (e.g., Basu, 1997; Ball and Shivakumar, 2005; Byzalov and Basu, 2016) and estimate the following piece-wise linear balance sheet model:

$$BDE_{it} = \beta_1 \Delta AR_{it} + \beta_2 D\Delta AR_{it} + \beta_3 \Delta AR_{it} \times D\Delta AR_{it} + \beta_4 WO_{it} + \omega_i + \epsilon_{it} \qquad (7)$$

where *DΔAR* is an indicator for a decline in accounts receivable. Prior research suggests that a decline in value-generating items such as cash flows, sales revenue, or number of employees can indicate bad news (e.g., Ball and Shivakumar, 2005; Byzalov and Basu, 2016; Banker et al., 2017). We follow this logic and deploy *DΔAR* as a bad news indicator. For instance, if we view receivables as “loans” that suppliers offer to their clients, a decline could be viewed as a sign of low performance (Basu et al., 2020). Also, because receivables are often a fraction of sales revenue, a decline in receivables could indicate a decline in overall demand. *DΔAR* is also positively correlated with future write-offs in our sample, suggesting that *DΔAR* predicts low collectability. We predict that, under conservatism, BDE increases more when receivables increase but does not decrease as much when receivables decline. Hence, β_3 would be negative.

We also estimate similar piecewise-linear income statement and Jones models. For those models, we use a sales decline indicator as the bad news indicator because sales revenue, instead of receivables, is used in those models.[17] We predict the coefficient on the interaction term to be negative under a conservative reporting system (because we model BDE as a positive number, the sign is flipped from the typical earnings asymmetric timeliness model).

[17] Asymmetry in bad debt expense cannot be explained by a cost stickiness argument as there are no resource allocations by the firm, in contrast to cost of goods sold or other SG&A expenses that involve resources.

3.3 Expected versus unexpected write-offs

As discussed above, the income statement approach generates BDE as a percentage of sales, expecting that a certain fraction of sales will be uncollectible and written off. Thus, although write-offs are not explicitly included in the income statement model, their expected portion should have already been considered when firms determine the percentages used to estimate BDE. The balance sheet approach, in contrast, takes into account both expected write-offs and the unexpected events that occurred during the fiscal period that led to unexpected write-offs. Thus, compared with the income statement model, the additional explanatory power of the balance sheet model should mainly come from unexpected write-offs.

To test this prediction, we decompose write-offs into their expected and unexpected components. Because write-offs arise when a customer is not able to pay its beginning payables (i.e., our focal firm's beginning receivables) and/or its current-period purchases (i.e., our focal firm's current-period sales), we estimate the following model to capture the average relation between write-offs and its two sources:

$$WO_{it} = \lambda_{j0} + \lambda_{j1}AR_{it-1} + \lambda_{j2}SALE_{it} + \epsilon_{it} \tag{8}$$

where subscript j indicates 2-digit SIC industry, and we estimate model (8) by industry to allow the coefficients to vary across industries.

We note that, because the coefficients reflect the average associations, they do not capture the unexpected, firm-specific bad news. The unexpected news is captured by the residual. Thus, the expected and unexpected write-offs are estimated as the predicted value and the residual of model (8), respectively. We then replace WO in model (5) by its expected and unexpected components and estimate the regression below:

$$BDE_{it} = \beta_1\Delta AR_{it} + \beta_2 EWO_{it} + \beta_3 UWO_{it} + \omega_i + \epsilon_{it} \tag{9}$$

3.4 Supply chain finance and bad debt expense

As discussed earlier, adopting SCF may affect the percentage of receivables used to determine BDE as well as the asymmetry in BDE. To test this prediction, we first introduce an indicator variable, *SCF*, that equals one if a firm belongs to a high SCF industry, and zero otherwise. Our first measure of SCF adoption is at the industry level because U.S. firms are not required to disclose SCF activities in their financial statements, and hence, firm-level SCF data is often not available. Specifically, we classify industries as having high levels of SCF based on PwC's SCF Barometer (2018/2019), which finds that more than 10 percent of their survey participants in consumer goods, transportation, and manufacturing industries have adopted SCF, and hence, designates them as high SCF industries.[18]

We interact *SCF* with ΔAR, $D\Delta AR$, and $\Delta AR \times D\Delta AR$, and add them to the piece-wise linear model (7) as follows.

$$BDE_{it} = \beta_1 \Delta AR_{it} + \beta_2 D\Delta AR_{it} + \beta_3 \Delta AR_{it} \times D\Delta AR_{it} + \beta_4 \Delta AR_{it} \times SCF_i + \beta_5 D\Delta AR_{it} \times SCF_i + \beta_6 \Delta AR_{it} \times D\Delta AR_{it} \times SCF_i + \beta_7 WO_{it} + \omega_i + \epsilon_{it} \quad (10)$$

We do not include the main effect of *SCF* because it has no variation within each firm and is subsumed by the firm fixed effects. To fully test our prediction, we estimate the regression above for the full sample period as well as separately for periods before and after 2008. Because SCF gained popularity mainly after 2008, we predict the coefficient on $\Delta AR \times SCF$ to be negative and the coefficient on $\Delta AR \times D\Delta AR \times SCF$ to be positive for the period after 2008, but not before 2009 (i.e., the test on the pre-2009 subsample could serve as a falsification test).

Our second measure of SCF adoption is a firm-level indicator, *HIGH_SCF*, that refines the industry-level indicator by further taking into account the change in days sales outstanding

[18] We classify the industries based on SIC codes. We consulted the authors of PwC's SCF Barometer (PwC 2018/2019) to ensure our classification is correct.

(DSO). While we cannot directly observe SCF adoptions, we expect that SCF adopters should experience large decreases in DSO around 2008. Thus, *HIGH_SCF* equals one if a firm is in the high SCF industries and its decrease in DSO around 2008 is in the top quartile, and zero otherwise. We then replace *SCF* in model (10) with *HIGH_SCF* to test its effect on BDE.

4. Sample selection and descriptive statistics

4.1 Sample selection

We begin with the Schedule II disclosures used by Jackson and Liu (2010) and Canace et al. (2016) which provide allowance for uncollectible accounts data from 1980-2010 for the 750 domestic firms on Compustat in 2002 with the largest unscaled gross trade accounts receivable.[19] The data consists of 8,015 observations for 452 firms with available Schedule II information during this period. Next, we extend the dataset to 2018 using procedures similar to the prior papers. Specifically, to obtain firms' Schedule II data for the period 2011 to 2018, we identify the 750 domestic firms on Compustat in 2011 with the largest unscaled gross trade accounts receivable. We exclude utilities, financial institutions, insurance companies, credit card companies, retailers, hotels, and leasing companies industries for a loss of 152 firms.[20] Of the 598 firms in the remaining industries, we are able to obtain 3,192 observations for 492 firms with available Schedule II information during this period.

Thus, we start with a combined sample of 11,207 observations for 737 firms with available Schedule II data over the period 1980-2018. We then truncate the sample to begin in

[19] Write-offs, BDE, and recoveries of previously written-off accounts must all be obtained from Schedule II of firms' Form 10-K because Compustat does not collect these items. We are grateful to Professor Jackson for making this data available to us for this study.
[20] We eliminate utilities, financial institutions, and insurance companies because they face regulatory forces that other firms do not face. We eliminate credit card companies, retailers, and hotels because their receivables are weighted toward consumer receivables which differ from trade (business) receivables in several important respects (e.g., transaction size, incentives for prompt payment, and bankruptcy frequency). We eliminate leasing companies because they hold outstanding loans rather than outstanding trade receivables.

1988 and end in 2017 due to data requirements for our regression variables.[21] This results in 10,240 observations for 737 firms. Next, we remove observations with missing Compustat and Schedule II data for variables across our bad debt expense models to provide constant samples for model comparisons. The resulting sample for analysis consists of 8,967 observations for 720 firms over the period 1988-2017.

4.2 Summary statistics

Table 1 presents the summary statistics of our sample. We provide variable definitions in Appendix A. Panel A reports that the mean of *BDE* is 0.41% of average total assets, which is equivalent to 28.7% of the mean of *ΔAR* (1.43%) and 0.3% of the mean of *SALE* (133.06%). *BDE* is also highly right-skewed as its mean is slightly larger than its third quartile (0.40%), which suggests that most firms recognize low BDE while some firms recognize much higher BDE when business conditions are bad. The summary statistics of *BDE* and *WO* are very close to each other, and their correlations in Panel B are high (Pearson correlation = 0.930, Spearman correlation = 0.763), suggesting that write-offs have a major effect on BDE. By contrast, the correlations between *BDE* and *ΔAR* (Pearson correlation = 0.211, Spearman correlation = 0.156) and between *BDE* and *SALE* (Pearson correlation = 0.116, Spearman correlation = 0.320) are lower, indicating that, if write-offs are not included, balance sheet and income statement models may not explain BDE well.

5. Empirical results

5.1 Univariate evidence

Before reporting the regression results, we first provide some model-free, univariate evidence of the relation between BDE and the explanatory variables from each model discussed

[21] Cash flow data is available in Compustat beginning in 1988. Also, we include the one year lead of write-offs (WO_{t+1}) in some regressions, which requires us to end the sample period at 2017.

above. Such model-free evidence helps us identify the potential asymmetry that stems from write-offs and, more generally, conservatism.

Figure 2, Panel A focuses on the balance sheet model and presents a scatter plot of BDE against *ΔAR*. We plot the linear trend line (dashed line) and locally weighted scatterplot smoothing (LOWESS) curve (solid line), which helps us assess the relation between BDE and *ΔAR* parametrically and nonparametrically, respectively. The linear trend line has a positive slope, suggesting that, on average, firms report higher BDE when receivables increase. In contrast, the LOWESS curve shows that the relation is V-shaped. When *ΔAR* is positive, i.e., receivables increase from the prior year, BDE increases with *ΔAR*, consistent with the linear trend line. However, when receivables decline, the relation between BDE and *ΔAR* becomes negative. This finding is consistent with Basu et al. (2020) who find that the relation between loan loss provision and the change in nonperforming loans is V-shaped.

The V-shaped relation supports our prediction that conservative adjustments such as write-offs lead to an asymmetry in BDE, and suggests that using a linear function to represent the relation is problematic. In particular, a decline in receivables can serve as an indicator of bad news,[22] and the magnitude of the decline indicates the severity of the news (Byzalov and Basu, 2016). Therefore, following the prior literature on conservatism (e.g., Basu, 1997; Basu et al., 2020), we argue that BDE could increase when receivables decrease for two reasons. First, a receivables decline may indicate that customers are in financial and/or operating difficulties, which can impair their ability to pay for the credit purchases made in the prior periods. When

[22] A decline in receivables could stem from either a decline in credit sales or an increase in cash collection. While a decline in credit sales indicates bad news, an increase in cash collection may be neutral or even good news. Because firms usually do not disclose credit sales or cash collection data, we cannot directly assess the relative importance of these two channels. However, the high correlation between change in receivables and change in sales (0.55, *p*-value < 0.01) suggests that credit sales play an important role.

customers fail to pay, the firm would have to write off the associated receivables and increase BDE under the balance sheet approach. Second, when customers are less likely to pay, conservatism requires managers to increase the percentages used to estimate the allowance, which in turn, could increase BDE.

Figure 2, Panel B turns to the income statement model and plots BDE against sales revenue. We find that both the linear trend line and the LOWESS curve suggest a positive relation between BDE and sales. The two curves are close to each other, and there is no evidence of asymmetry. Although a lack of asymmetry could suggest that BDE is not conservative on average, another plausible explanation is that, as discussed above, most firms use the balance sheet approach, rather than the income statement approach, to report BDE. Thus, the asymmetry caused by conservatism would not be reflected in Panel B.

Figure 2, Panel C presents a scatterplot of BDE against the change in adjusted sales revenue based on the modified Jones model.[23] We find patterns similar to those in Panel A. Again, the linear trend line has a positive slope, but the LOWESS curve shows a V-shaped relation. The similarity between Panels A and C supports the assumption underpinning the Jones model, i.e., changes in sales can proxy for the change in economic circumstances that drives the change in working capital accounts. However, the V-shaped relation also highlights that the modified Jones model suffers from severe bias stemming from conservatism, and such bias could be particularly concerning when economic circumstances are bad.

Finally, Figure 2, Panel D plots the relation between BDE and write-offs. We find that the linear trend line and LOWESS curve indicate that the relation is positive and largely linear. The scatter plot also shows that the relation between BDE and write-offs is very strong as the

[23] In unreported results, we also plot BDE against the change in sales revenue (based on the original Jones model) and find similar patterns.

slope of the linear trend line is slightly less than 1.[24]

Overall, our model-free evidence highlights that (1) the standard linear models such as the Jones and modified Jones models are misspecified as they fail to take the asymmetry into account, and (2) write-offs can play an important role in explaining BDE. Thus, it is important to refine the linear accrual models and incorporate conservative adjustments such as write-offs.

5.2 Multiple regressions

5.2.1 Evidence from the balance sheet model

We now use regressions to examine the relation between BDE and its determinants. Table 2 reports the results from the balance sheet model (i.e., equation (5)). In column 1, we only include the change in receivables as an explanatory variable but not write-offs. The coefficient on ΔAR is positive and significant at the 1 percent level, consistent with the linear trend line observed in Figure 2, Panel A. In terms of explanatory power, although the adjusted R^2 is 0.734, much of it comes from the firm fixed effects, and the adjusted within R^2 (i.e., the percentage of variation explained by the covariates after excluding firm fixed effects) is only 0.009. Thus, the balance sheet model without write-offs does not explain BDE well.

In column 2, we add write-offs to the regression. We find that the coefficient on write-offs is also positive and significant at the 1 percent level. The adjusted within R^2 increases substantially to 0.592, confirming that write-offs play a major role in BDE.[25] This finding also suggests that the "complete" balance sheet model with write-offs has good explanatory power. Following McNichols and Wilson (1988), we further include write-offs in period t+1 in column

[24] Equation (2) suggests that a $1 increase in write-offs should corresponds to a $1 increase in BDE. While a slightly less than 1 slope is not entirely consistent with this prediction, we note that it is consistent with the findings in the prior literature (e.g., McNichols and Wilson, 1988).

[25] For this analysis and the income statement and modified Jones models discussed below, we find consistent results when replacing write-offs in period t with write-offs in period t+1.

3. The coefficient is again positive and significant at the 1 percent level, consistent with the prior literature. The adjusted within R^2 is further improved to 0.663. However, because adding future write-offs introduces information that is unavailable to managers, this model may not represent the true BDE-generating process, even though it has better explanatory power.

In columns 4 to 6, we estimate the piece-wise linear regression (7) and its extensions. We find that the coefficient on the interaction term, $D\Delta AR \times \Delta AR$, is negative and significant at the 1 percent level in all three columns, consistent with conservatism leading to an asymmetric relation between BDE and ΔAR. In column 4, the F-test suggests that the sum of the coefficients on ΔAR and $D\Delta AR \times \Delta AR$ is -0.030 and significant at the 1 percent level, consistent with the V-shaped relation shown Figure 2, Panel A. The adjusted within R^2 of column 4 is 0.029, which has tripled from column 1 but is still small compared to column 2. This observation suggests that the piece-wise linear structure cannot completely replace write-offs. When we include write-offs and future write-offs in columns 5 and 6, the adjusted within R^2 again increases to 0.600 and 0.667, respectively. We also find that the coefficient on $D\Delta AR \times \Delta AR$ decreases by almost half when we include write-offs, which is perhaps not surprising because a part of the asymmetry comes from write-offs (i.e., receivables can be written down but not up). However, the coefficient on $D\Delta AR \times \Delta AR$ remains significant at the 1 percent level even if write-offs are added to the regression, indicating that there are ways other than through write-offs for conservatism to induce asymmetry. For example, as discussed above, managers may increase the percentages used to estimate allowances when there is bad news.

We now revisit the asymmetric pattern shown in Figure 2, Panel A. We note that a well-specified model should be able to capture the asymmetry, and thus, if we plot the residuals from the model against ΔAR, their relation would be symmetric. Figure 3 plots the relations between the mean residuals from the six specifications estimated in Table 2 against ΔAR.[26] When neither write-offs nor the piece-wise linear structure is included, we again find a V-shaped relation between the residuals and ΔAR. The V shape flattens when we include write-offs and disappears when the piece-wise linear structure is further included. Because residuals from accrual models are often used as a proxy for earnings management, we caution that the standard linear model would misclassify conservative adjustments as earnings management. Thus, for example, when researchers test the association between such residuals and potential determinants of earnings management, the results would be biased if those determinants are associated with conservatism. Overall, Figure 3 highlights the importance of including conservatism when modeling accrual-generating processes (Basu, 1997; Ball and Shivakumar, 2005, 2006; Byzalov and Basu, 2016; Larson, Sloan and Zha Geidt, 2018).

5.2.2 Evidence from the income statement model

Table 4 presents the results of the income statement model. In column 1, we estimate equation (6) and find that the coefficient on sales is 0.003 and significant at the 1 percent level. This finding suggests that managers estimate 0.3 percent of total sales as BDE on average if firms have been using the income statement approach. The adjusted R^2 of the model is 0.741, and again, it is mainly driven by the firm fixed effects. The adjusted within R^2 is only 0.035, indicating that the income statement model does not perform well.

In column 2, we consider an extension of the basic income statement model by including write-offs. The adjusted within R^2 increases to 0.586. As discussed, if firms indeed use the income statement approach, write-offs should have no direct effect on BDE, and hence, the inclusion of write-offs would have little impact on adjusted within R^2. Thus, the big increase in

---

[26] Firm-year observations are divided into 100 equal frequency bins sorted on ΔAR for calculating mean residuals. Gelman et al. (2000) recommend examining binned residuals as an intuitive check of model adequacy.

adjusted within R^2 supports the prediction that the balance sheet approach, rather than the income statement approach, is more widely used. In column 3, we again add write-offs in year t+1 as an explanatory variable and find that the adjusted within R^2 increases to 0.658.

In columns 4 to 6, following Byzalov and Basu (2016), we estimate piece-wise linear models by including the interaction between sales and an indicator for sales decline. We find that the results in these columns are similar to those in columns 1 to 3, and the coefficient on the interaction term is statistically insignificant in all three columns. Thus, consistent with Figure 2, Panel B, there is no asymmetry. Moreover, compared to column 3, the adjusted within R^2 in column 6 decreases by 0.001, again suggesting that allowing for the potential asymmetry does not improve explanatory power. Overall, our findings suggest that managers do not use the income statement approach to determine the reported BDE, and hence, conservatism is not captured well by the piece-wise linear structure of an income statement model.

5.2.3 Evidence from the modified Jones model

Table 4 presents the results of the modified Jones model (i.e., equation (4)). In column 1, we estimate the original modified Jones model. We find that the coefficient on *ΔADJ_SALE* is positive and significant at the 1 percent level, and that the adjusted within R^2 is 0.011. The small adjusted within R^2 again suggests that the explanatory power is low. When we add write-offs to the regression in column 2, the adjusted within R^2 increases to 0.591, which indicates that adding write-offs to the modified Jones model can substantially improve its performance.

In columns 3 to 6, we further include future write-offs and/or a piece-wise linear structure. We find that the coefficient on the interaction term, *DΔADJ_SALE* × *ΔADJ_SALE*, is negative and significant at the 1 percent level, consistent with our prediction and the results in Table 2. In column 4, the F-test shows that the sum of the coefficients on *ΔADJ_SALE* and

DΔADJ_SALE × *ΔADJ_SALE* is negative and significant at the 1 percent level, consistent with the V-shaped relation shown in Figure 2, Panel C. Overall, we again find that including the piece-wise linear structure can improve the explanatory power of the model, although such improvement is small compared with that from write-offs.

5.2.4 Model comparison

Now we compare the results in Tables 2 to 4. There are three main takeaways. First, we find that for all models, including write-offs as an explanatory variable significantly improves the adjusted within R^2, so it is important to include them in the regressions. Second, while the "complete" balance sheet model (column 2 in Table 2) outperforms the income statement model (column 1 in Table 3) and the modified Jones model (column 1 in Table 4) because it includes write-offs, the difference becomes minimal when write-offs are also included in the other two models. This suggests the need to include write-offs in accrual models. Third, for both Tables 2 and 4, the magnitude of the coefficient on the interaction term decreases by about half when write-offs are included (column 4 vs. column 5). In other words, write-offs explain roughly half of the asymmetry in BDE, and the remaining half can be captured by a piece-wise linear structure, so it is beneficial to further include the structure.

In Figure 4, we further compare the performance of the models by plotting the average predicted BDE from each model (i.e., the expected value from the regressions) against the average actual BDE in each year. For each model, we examine specifications with and without write-offs to show the importance of incorporating write-offs into the model. In Panel A, we find that, when write-offs are included, the predicted BDE from the balance sheet model and the actual BDE are very close to each other, suggesting that the model explains the actual data well. However, the gap between the predicted and actual BDE widens when we drop write-offs from the model and estimate BDE using the change in receivables only (i.e., column 1 in Table 2).

In Panels B and C, we examine the income statement and modified Jones models. Similar to the balance sheet model, both models explain the time-series variations in BDE well only if write-offs are included. Another interesting observation is that the actual BDE and the predicted BDE from the modified Jones models often move in the opposite direction. For example, during the early 2000s recession and the 2007-08 financial crisis, the actual BDE went up (relative to the years around the recessions) but the predicted BDE from the modified Jones model went down. The actual BDE went up because bad business conditions such as recessions often make it harder for customers to pay, and hence, firms need to write off more and report higher BDE. However, the modified Jones model predicts BDE based on the average positive relation between change in adjusted sales and BDE. Because sales often decline during recessions, the predicted BDE also decreases. Hence, an important implication of this finding is that standard linear accrual models such as the modified Jones model would severely overestimate discretionary accruals (i.e., underestimate BDE) during recessions because the high write-offs would bias the residuals downwards.

5.3 Decomposing write-offs

Next, we decompose write-offs using a regression specified as equation (8). Expected write-offs are computed as the predicted value of write-offs from the regression, and unexpected write-offs are measured as the residual. Before reporting the estimation results with the components of write-offs, we review some descriptive evidence.

We assess the time-series variation of write-offs as well as the expected and unexpected components in Figure 1. As seen, the write-offs, unexpected write-offs, and BDE are larger during recessions, which is again not surprising because recessions often cause businesses to perform worse, and hence, lead to more defaults. The large increases in write-offs during recessions are mainly driven by the increases in unexpected write-offs rather than expected write-offs. This is because the expected write-offs only reflect the average portion of receivables that firms need to write off during the entire sample period, but does not capture market-wide negative events such as recessions.

Table 5 reports the estimation results of regression (9).[27] In column 1, we estimate a baseline model where neither of the write-off components is included, and the adjusted within R^2 is only 0.016. We add the expected write-offs in column 2, and the adjusted within R^2 increases to 0.058 (i.e., an increase of 0.042). However, when we further include the unexpected write-offs, the adjusted within R^2 increases to 0.502 (i.e., an additional increase of 0.444). This finding suggests that the contribution of the unexpected write-offs to the incremental explanatory power is about 10 times higher than that of the expected write-offs, consistent with our prediction. The magnitude of the coefficient on the asymmetry term decreases by 0.010 when expected write-offs are included and decreases by another 0.013 when unexpected write-offs are included, suggesting that both components contribute to the asymmetry in BDE.

5.4 The effect of supply chain finance on bad debt expense

Panels A and B of Figure 5 plot the trends in BDE for high and low SCF industries, respectively. Consistent with our prediction in Section 2, there is a decrease in BDE for the high SCF industries after the 2007-08 financial crisis. However, we do not observe a similar decrease in the low SCF industries. This finding suggests that the decreasing trends observed in Figure 1 are mainly driven by the high SCF industries.

Next, we turn to regression analysis. Table 6 reports our estimation results of regression

[27] The sample size decreases from 8,967 to 8,073 for this regression because our estimation of write-offs in model (8) requires the lag of gross accounts receivable (AR_{t-1}).

(10). Panel A presents the full sample analysis. To ensure robustness, we estimate two specifications by varying the write-offs terms included as explanatory variables. In both columns, the coefficients on *ΔAR×SCF* and *ΔAR×DΔAR×SCF* are statistically insignificant, suggesting that the BDE of high SCF and low SCF industries are similar on average. However, because SCF became more widely adopted only after the financial crisis, estimating the effect of SCF using the full sample may suffer from low test power.

Panel B conducts the subsample analysis by partitioning the full sample period into pre-2009 and post-2008 periods. The results from the pre-2009 sample are similar to those from the full sample, and the coefficients on *ΔAR×SCF* and *ΔAR×DΔAR×SCF* are again insignificant for both specifications. The insignificant result suggests that firms in the high and low SCF industries had similar BDE initially, and hence, any difference identified in the post-2008 period can be attributed to the use of SCF instead of time-invariant industry characteristics. For the post-2008 sample, in contrast, we find that coefficients on *ΔAR×SCF* and *ΔAR×DΔAR×SCF* become negative and positive, respectively, and are statistically significant. These findings support our prediction.

Table 7 reports the results of replacing industry-level SCF indicator with firm-level SCF indicator, *HIGH_SCF*. Again, we find that insignificant results from the full sample and pre-2009 subsample analyses. In contrast, for post-2008 subsample, we find significant coefficients on *ΔAR×HIGH_SCF* and *ΔAR×DΔAR× HIGH_SCF*, and their signs are again consistent with our expectation and those reported in Table 7. Finally, we also conduct a Chi-squared test to compare the coefficients across subsamples. We find that difference in the coefficient on *ΔAR×DΔAR× HIGH_SCF* is significant at the 1 percent level for the model excluding future write-offs and 5 percent level for the model with future write-offs.

5.5 Implications for earnings management

In further testing, we examine how well the models detect BDE management by estimating the probability of making a Type I error (i.e., mistakenly reject the null hypothesis that there is no BDE management) and Type II error (i.e., fail to reject the null hypothesis when there is indeed BDE management). In particular, we conduct simulations by following steps similar to Dechow et al. (2012), Byzalov and Basu (2016), and Collins et al. (2017).

For Type I error, we randomly select 100 "suspect BDE management" observations from either the full sample or a subsample, and then create an indicator variable *PART* that equals 1 for the suspect observations and 0 for the other observations. We then add *PART* into our models as an additional explanatory variable, re-estimate the models, and check if the coefficient on *PART* is statistically significant at the 5 percent level based on a two-tailed test. We examine both the balance sheet and modified Jones models by varying the inclusion of write-offs and/or the piece-wise linear structure.[28] We simulate 1000 times and count the number of significant coefficients on *PART*. Because the suspect observations are randomly selected and unrelated to "true" BDE management, the null hypothesis that the coefficient on *PART* is 0 would be rejected only if a Type I error occurs, i.e., the rejection rate should be about 5 percent (Dechow et al., 2012; Byzalov and Basu, 2016).

Table 8, Panel A presents the simulation results. We find that, when suspect observations are selected from the full sample, all models make a Type I error in about 5 percent of simulations, consistent with the nominal rejection rate. However, when the suspect observations

[28] Specifically, we consider (1) the original modified Jones model without write-offs (i.e., Table 4, model 13), (2) modified Jones model with write-offs (i.e., Table 4, model 14), (3) modified Jones model with piece-wise linear structure (i.e., Table 4, model 16), (4) modified Jones model with both write-offs and piece-wise linear structure (i.e., Table 4, model 17), (5) balance sheet model without write-offs (i.e., Table 2, model 1), (6) balance sheet model with write-offs (i.e., Table 2, model 2), (7) balance sheet model with piece-wise linear structure (i.e., Table 2, model 4), and (8) balance sheet model with both write-offs and piece-wise linear structure (i.e., Table 2, model 5).

are selected from the extreme *WO* deciles, top decile, or bottom decile, the models without write-offs have a rejection rate greater than 65 percent, regardless of whether the piece-wise linear structure is included or not. In contrast, for the models that incorporate *WO*, we find that the rejection rates are again close to the 5 percent. These findings suggest that the models without *WO* frequently make Type I errors by misclassifying extreme write-offs as BDE management. Next, we select the suspect observations from the extreme *ΔADJ_SALE* deciles, top decile, or bottom decile, and find that including the piece-wise linear structure can substantially resolve the over-rejection problem. This is likely because the piece-wise linear structure is designed to capture the asymmetry in *ΔADJ_SALE*. Thus overall, we find that both write-offs and the piece-wise linear structure help avoid Type I error.

For Type II error, we randomly select 100 suspect BDE management observations from the full sample and decrease their BDE by 0.09% (i.e., 10 percent of the standard deviation of BDE).[29] Again, we create an indicator variable *PART* that equals 1 for the suspect observations and 0 for the other observations and then re-estimate the models to check if the coefficient on *PART* is statistically significant at the 5 percent level based on a one-tailed test. We again simulate 1000 times and report the rejection rates in Table 8, Panel A. We find that the rejection rates of models without write-offs are about 60 percent. Adding write-offs to the models can improve the rejection rate to about 85 percent.[30] In contrast, adding the piece-wise linear structure does not affect the rejection rate.

Table 8, Panel B conducts a similar simulation analysis but examines two subsamples:

---

[29] We choose 10 percent of the standard deviation of BDE because prior studies (e.g., Dechow et al., 2012, Byzalov and Basu, 2016) that focus on total accruals management often change accruals by 1 percent of total assets, which is approximately 10 percent of the standard deviation of accruals. For instance, Dechow et al. (2012) report that the standard deviation of accruals (scaled by total assets) in their sample is 0.124.

[30] Prior research explains that the ex ante power of a test should be at least 80% in order to have the precision to provide reliable inferences (Dechow et al., 2012, p. 308).

(A) a subsample comprising firms in the SCF industries in the post-2008 period and (B) the rest of the full sample. Due to the differential adoption of SCF, as shown in Table 6, Panel B, these two subsamples have differential BDE asymmetry, and hence, analyzing them separately can potentially further improve BDE management detection. In particular, we focus on the *ΔADJ_SALE* decile-based simulations for the balance sheet model because they make a Type I error more frequently in Table 8, Panel A (e.g., the rejection rate is 10.4 percent after incorporating write-offs and the piece-wise linear structure). We find that the rejection rate decreases to close to 5 percent for the subsamples after incorporating write-offs and/or the piece-wise linear structure, thus improving Type I error. We also find that the Type II error improvements for the subsample analysis are similar to those from the full sample.

5.6 Additional analysis

Finally, we conduct three tests to check the robustness of our results by including prior-year receivables changes and/or write-offs, as well as studying the effect of fourth-quarter sales as in Byzalov and Basu (2016). As discussed in Appendix C, our results are robust to these tests.

6. Conclusions

In this study, we show the importance of modeling accruals based on accounting methods and taking real transactions into account. We develop models based on income statement and balance sheet approaches and compare them with the standard linear accruals models such as the modified Jones model (Dechow et al., 1995). We find that the balance sheet model has the best explanatory power because it contains write-offs as an independent variable. We find that the relation between BDE and change in accounts receivable (as well as change in adjusted sales) is V-shaped due to conservatism. Adding write-offs and piece-wise linear structures to the models can flatten the pattern and better explain BDE.

Further analyses suggest that real transactions such as the SCF affect the risk of working capital, and hence, influence how firms determine accruals. If some real transactions are more widely adopted in some industries or years, then it is important to model these differences. Otherwise, the accrual-generating process is misspecified, and important managerial implications cannot be derived.

Modeling the accrual-generating process by tying it to accounting methods and incorporating real transactions also has important implications for the literature on earnings management. Prior studies often use the residuals from the standard linear accruals models as a proxy for accruals-based earnings management. However, our paper shows that the standard linear models would pool the "true" discretionary accruals with the largely nondiscretionary write-offs in the residuals, causing a Type I error and a bias to the earnings management measure. Moreover, if real transactions such as SCF are not modeled, the accruals models would mistakenly classify the legitimate accounting judgments based on such transactions as earnings management. To overcome these issues, future studies can model other accruals items using item-specific accounting methods. Future research can also explore other real transactions.

References

Badertscher, B.A., Burks, J.J. and Easton, P.D., 2012. A convenient scapegoat: fair value accounting by commercial banks during the financial crisis. *The Accounting Review*, *87*(1), pp.59-90.

Ball, R. and Shivakumar, L., 2005. Earnings quality in U.K. private firms: comparative loss recognition timeliness. *Journal of Accounting and Economics*, *39*(1), pp.83-128.

Ball, R. and Shivakumar, L., 2006. The role of accruals in asymmetrically timely gain and loss recognition. *Journal of Accounting Research*, *44*(2), pp.207-242.

Barker, R. and McGeachin, A., 2015. An analysis of concepts and evidence on the question of whether IFRS should be conservative. *Abacus*, *51*(2), pp.169-207.

Basu, S., 1997. The conservatism principle and the asymmetric timeliness of earnings1. *Journal of Accounting and Economics*, *24*(1), pp.3-37.

Basu, S., Hwang, L.S. and Jan, C.L., 2002. Auditor conservatism and quarterly earnings. Working paper.

Basu, S. and Waymire, G.B., 2010. Sprouse's what-you-may-call-its: Fundamental insight or monumental mistake? *Accounting Historians Journal*, *37*(1), pp.121-148.

Basu, S., Vitanza, J. and Wang, W., 2020. Asymmetric loan loss provision models. *Journal of Accounting and Economics*, *70*(2-3), 101359.

Beatty, A. and Liao, S., 2011. Do delays in expected loss recognition affect banks' willingness to lend?. *Journal of Accounting and Economics*, *52*(1), pp.1-20.

Beatty, A. and Liao, S., 2014. Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, *58*(2-3), pp.339-383.

Beck, A., Gilstrap, C., Rippy, J. and Vansant, B., 2020. Strategic reporting by nonprofit hospitals: An examination of bad debt and charity care. Working paper.

Beck, P.J. and Narayanamoorthy, G.S., 2013. Did the SEC impact banks' loan loss reserve policies and their informativeness?. *Journal of Accounting and Economics*, *56*(2-3), pp.42-65.

Benston, G.J., Carmichael, D.R., Demski, J.S., Dharan, B.G., Jamal, K., Laux, R., Rajgopal, S. and Vrana, G., 2007. The FASB's conceptual framework for financial reporting: A critical analysis. *Accounting Horizons*, *21*(2), pp.229-238.

Bernard, V.L. and Skinner, D.J., 1996. What motivates managers' choice of discretionary accruals?. *Journal of Accounting and Economics*, *22*(1-3), pp.313-325.

Bushman, R.M. and Williams, C.D., 2012. Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking. *Journal of Accounting and Economics*, *54*(1), pp.1-18.

Bushman, R.M. and Williams, C.D., 2015. Delayed expected loss recognition and the risk profile of banks. *Journal of Accounting Research*, *53*(3), pp.511-553.

Byzalov, D. and Basu, S., 2016. Conditional conservatism and disaggregated bad news indicators in accrual models. *Review of Accounting Studies*, *21*(3), pp.859-897.

Canace, T.G., Hatfield, R.C. and Jackson, S.B., 2016. Conservatism and Staff Accounting Bulletin no. 108. *Accounting, Organizations and Society*, *52*, pp.15-31.

Cecchini, M., Jackson, S.B. and Liu, X., 2012. Do initial public offering firms manage accruals? Evidence from individual accounts. *Review of Accounting Studies*, *17*(1), pp.22-40.

Chase, C.W., 2013. *Demand-driven forecasting: a structured approach to forecasting*. John Wiley & Sons.

Chuk, E., Lourie, B., and Yoo, I.S., 2021. The determinants and consequences of reverse

factoring: Early evidence from the UK. Working paper.
Cohen, D.A., Dey, A. and Lys, T.Z., 2008. Real and accrual-based earnings management in the pre- and post-Sarbanes-Oxley periods. *The Accounting Review*, *83*(3), pp.757-787.
Collins, D.W., Pungaliya, R.S. and Vijh, A.M., 2017. The effects of firm growth and model specification choices on tests of earnings management in quarterly settings. *The Accounting Review*, 92(2), pp.69-100.
Dechow, P.M. and Dichev, I.D., 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review*, *77*(s-1), pp.35-59.
Dechow, P.M., Hutton, A.P., Kim, J.H. and Sloan, R.G., 2012. Detecting earnings management: A new approach. *Journal of Accounting Research*, 50(2), pp.275-334.
Dechow, P.M. and Skinner, D.J., 2000. Earnings management: Reconciling the views of accounting academics, practitioners, and regulators. *Accounting Horizons*, 14(2), pp.235-250.
Dechow, P.M., Sloan, R.G. and Sweeney, A.P., 1995. Detecting earnings management. *The Accounting Review*, *70*(2), pp.193-225.
Dichev, I.D., 2008. On the balance sheet-based model of financial reporting. *Accounting Horizons*, *22*(4), pp.453-470.
Dichev, I.D. and Tang, V.W., 2008. Matching and the changing properties of accounting earnings over the last 40 years. *The Accounting Review*, *83*(6), pp.1425-1460.
Elliott, J.A. and Hanna, J.D., 1996. Repeated accounting write-offs and the information content of earnings. *Journal of Accounting Research*, *34*, pp.135-155.
Fields, T.D., Lys, T.Z. and Vincent, L., 2001. Empirical research on accounting choice. *Journal of Accounting and Economics*, 31(1-3), pp.255-307.
Frankel, R., Kim, B.H., Ma, T. and Martin, X., 2020. Bank monitoring and financial reporting quality: The case of accounts receivable–based loans. *Contemporary Accounting Research*, 37(4), pp.2120-2144.
Gelman, A., Goegebeur, Y., Tuerlinckx, F. and Van Mechelen, I., 2000. Diagnostic checks for discrete data regression models using posterior predictive simulations. *Applied Statistics*, 49(2), pp.247-268.
Hofmann, E., Templar, S., Rogers, D., Choi, T.Y., Leuschner, R. and Korde, R.Y., 2021. Supply chain financing and pandemic: Managing cash flows to keep firms and their value networks healthy. *Rutgers Business Review*, *6*(1), pp.1-23.
Holthausen, R.W. and Watts, R.L., 2001. The relevance of the value-relevance literature for financial accounting standard setting. *Journal of Accounting and Economics*, *31*(1-3), pp.3-75.
Jackson, S.B. and Liu, X., 2010. The allowance for uncollectible accounts, conservatism, and earnings management. *Journal of Accounting Research*, *48*(3), pp.565-601.
Jones, J.J., 1991. Earnings management during import relief investigations. *Journal of Accounting Research*, *29*(2), pp.193-228.
Kaplan, S.E., 1985. The effect of combining compliance and substantive tasks on auditor consensus. *Journal of Accounting Research*, *23*(2), pp.871-877.
Kothari, S.P., Leone, A.J. and Wasley, C.E., 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, *39*(1), pp.163-197.
Krishnan, J., Wen, Y. and Zhao, W., 2011. Legal expertise on corporate audit committees and financial reporting quality. *The Accounting Review*, *86*(6), pp.2099-2130.
Larson, C., Sloan, R.G. and Zha Geidt, J., 2018. Defining, measuring and modeling accruals: a guide for researchers. *Review of Accounting Studies*, *23*(3), pp.827-871.

Lawrence, A., Sloan, R.G. and Sun, Y., 2013. Non-discretionary conservatism: Evidence and implications. *Journal of Accounting and Economics*, *56*(2-3), pp.112-133.
Lee, C.M.C., 2014. Performance measurement: An investor's perspective. *Accounting and Business Research*, *44*(4), pp.383-406.
Leone, A.J. and Van Horn, R.L., 2005. How do nonprofit hospitals manage earnings? *Journal of Health Economics*, *24*(4), pp.815-837.
McNichols, M. and Wilson, G.P., 1988. Evidence of earnings management from the provision for bad debts. *Journal of Accounting Research*, *26*(Supplement), pp.1-31.
O'Brien, P.C., 2009. Changing the concepts to justify the standards. *Accounting Perspectives*, *8*(4), pp.263-275.
Owens, E.L., Wu, J.S. and Zimmerman, J.L., 2017. Idiosyncratic shocks to firm underlying economics and abnormal accruals. *The Accounting Review*, *92*(2), pp.183-219.
PwC. 2018/2019. Supply Chain Finance Barometer Study 2018/2019.
Sommer, M. and O'Kelly, R. 2017. Supply chain finance: Riding the waves. United Kingdom.
Wang, Z, Wang, Q, Lai, Y, Liang, C. 2020. Drivers and outcomes of supply chain finance adoption: An empirical investigation in China. *International Journal of Production Economics*, 220 (107453).
Watts, R.L., 2003. Conservatism in accounting part I: Explanations and implications. *Accounting Horizons*, *17*(3), pp.207-221.
World Economic Forum. 2019. Trade Tech – A New Age for Trade and Supply Chain Finance, https://www.weforum.org/whitepapers/trade-tech-a-new-age-for-trade-and-supply-chain-finance.
Zang, A.Y., 2012. Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review*, *87*(2), pp.675-703.
Zhang, J., 2008. The contracting benefits of accounting conservatism to lenders and borrowers. *Journal of Accounting and Economics*, *45*(1), pp.27-54.

Appendix A

Variable Definitions

Variable	Definition
BDE_t	Bad debt expense obtained from 10-K Schedule II scaled by average total assets
ΔAR_t	Change in gross accounts receivable calculated as the change in receivables (in the current year t relative to the prior year t-1) plus the change in the allowance (in the current year t relative to the prior year t-1) scaled by average total assets
WO_t	Write-offs of uncollectible accounts receivable obtained from 10-K Schedule II scaled by average total assets
$ALLOW_t$	The ending balance of the allowance for uncollectible accounts receivable obtained from 10-K Schedule II scaled by average total assets
EWO_t	Expected write-offs of uncollectible accounts receivable scaled by average total assets, obtained from the industry estimation model
UWO_t	Unexpected write-offs of uncollectible accounts receivable scaled by *ATA*, calculated as WO_t minus EWO_t
$SALE_t$	Sales (net) scaled by average total assets
ΔADJ_SALE_t	Change in adjusted sales, calculated as current year adjusted sales minus the one year lag of adjusted sales, scaled by *ATA*. Adjusted sales is measured as $\Delta SALE_t$ minus ΔAR_t , where $\Delta SALE_t$ is calculated as current year sales minus the one year lag of sales scaled by average total assets
$D\Delta AR_t$	An indicator for decrease in receivables ($\Delta AR_t < 0$)
$D\Delta ADJ\_SALE_t$	An indicator for decrease in adjusted sales ($\Delta ADJ\_SALE_t < 0$)
SCF	An indicator for firm-year observations from the following industries where supply chain financing is expected to be more prevalent: consumer goods (SIC codes 20, 22, 23, 50, and 51), computer and office equipment (SIC code 3570), electronic computers (SIC code 3571), computer storage devices (SIC code 3572), computer terminals (SIC code 3575), computer communications equipment (SIC code 3576), computer peripheral equipment (SIC code 3577), manufacturing (SIC codes 25, 26, 27, and 39), and transportation equipment (SIC code 37)
HIGH_SCF	An indicator for firm-year observations where SCF=1 and ΔDSO is in the top quartile. ΔDSO is defined as the firm's average *DSO* during the pre-2009 period minus the firm's average DSO during the post-2008 period. *DSO*, or days sales outstanding, is calculated as 365 divided by accounts receivable turnover, where accounts receivable turnover is calculated as net sales divided by average accounts receivable
PART	An indicator variable set equal to 1 in firm-years during which systematic BDE-related earnings management is suspected and 0 for remaining observations in which no systematic BDE-related earnings management is expected

Appendix B

Bad Debt Expense Models in Prior Studies

A few prior studies also model BDE, and this appendix compares our models with theirs.

First, McNichols and Wilson (1988) model BDE based on a balance sheet approach as follows:

$$BDE_t = \alpha_0 + \alpha_1 ALLOW_{t-1} + \alpha_2 WO_t + \alpha_3 WO_{t+1} + \epsilon_t \tag{B1}$$

In equation (B1), BDE is assumed to be affected by the beginning allowance, current write-offs, and managers' expected future write-offs (proxied by write-offs in the next period). Unlike theirs, our model only includes allowance and current write-offs, but not future write-offs. Thus, we use information available at the time when BDE is estimated by the managers and avoid the look-ahead bias. This is also likely more consistent with current GAAP as BDE is determined based on whether it is probable that a loss has been incurred rather than an expectation that one will be incurred in the future (Basu et al., 2020).

Next, Leone and Van Horn (2005) and Beck, Gilstrap, Rippy, and Vansant (2020) focus on the BDE of hospitals and develop BDE models based on the income statement approach as follows:

$$\begin{aligned} \Delta BDE_t = \alpha_0 + \alpha_1 \Delta NetRevenue_t + \alpha_2 \Delta MedicareRevenue_t \\ + \alpha_3 \Delta MedicaidRevenue + \epsilon_t \end{aligned} \tag{B2}$$

As seen, their approach assumes BDE arises from net revenue, Medicare revenue, and Medicaid revenue, and they estimate a change model. Because we include firm fixed effects in our income statement models, our model becomes equivalent to their model (Angrist and Pischke, 2008).

Appendix C

Additional Tests

In this appendix, we summarize three additional tests that we conduct to strengthen the reliability of our empirical results.

First, prior studies in bank financial reporting often model loan loss provision (i.e., the BDE for banks) as a function of change in nonperforming loans in period t as well in periods t-1 and t-2 (e.g., Beatty and Liao, 2011, 2014; Bushman and Williams, 2012, 2015; Basu et al., 2020). Thus analogously, we expand equation (5) by further including changes in receivables in periods t-1 and t-2. We find that our main results still hold.

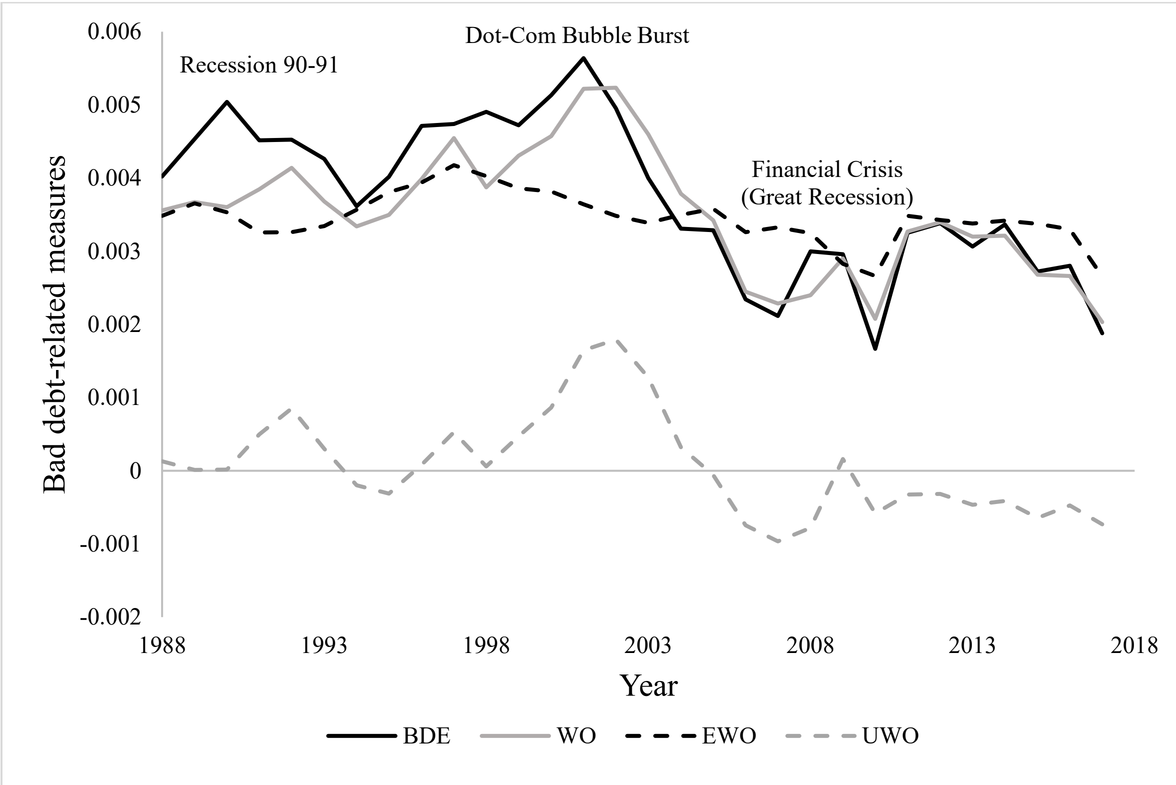
Second, Beck and Narayanamoorthy (2013) find that prior loan charge-offs (i.e., the write-offs for banks) are informative about current loan loss provisions and nonperforming loans. Thus analogously, we expand equation (5) by further including write-offs from periods t-1 and t-2. We again find consistent results.

Third, Byzalov and Basu (2016) find that working capital accruals exhibit incremental asymmetry with respect to change in sales in the fourth quarter. This is because, by the end of the year, many credit sales made in the earlier quarters may have already been collected and becomes less relevant to bad debt expense. Moreover, because the interim financial reports are reviewed but not audited, firms often make conservative adjustments at the end of the year to satisfy auditors' preference for conservative reporting (Elliot and Hanna 1996; Basu, Hwang, and Jan 2002). Thus, consistent with the prior literature, we also predict the fourth quarter sales to have an incremental effect on asymmetry beyond annual sales. To test our prediction, we extend the Jones model by further adding the change in fourth quarter sales, an indicator of fourth quarter sales decline, and their interaction. Change in fourth quarter sales is measured as sales in the fourth quarter of year t minus sales in the fourth quarter of year t-1 to remove seasonality

(Byzalov and Basu, 2016). We cannot use the change in adjusted fourth quarter sales because it requires a similar adjustment for the year-over-year change in receivables which would capture credit sales occurring over the year. We find that the coefficient on the interaction term is negative and significant at the 1 percent level, consistent with our prediction.

FIGURE 1

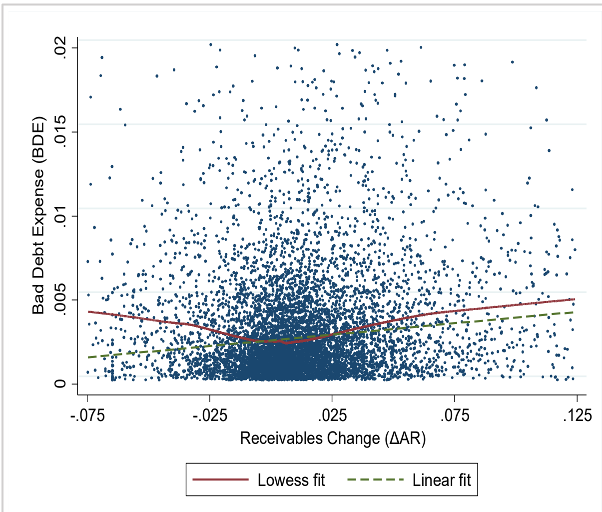
Plots of Bad Debt Expense and Write-offs over Time



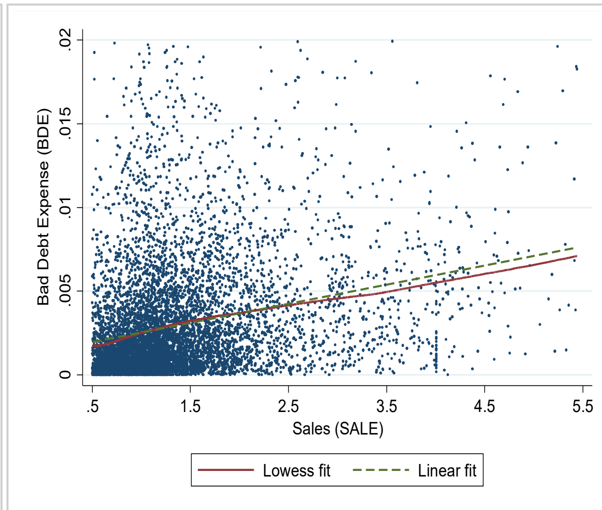
This figure plots the relationships between bad debt expense (BDE), write-offs (WO), expected write-offs (EWO), unexpected write-offs (UWO) and year for the sample period 1988 - 2017. All variables are scaled by average total assets. Bad debt expense and write-offs are obtained from firms' Schedule II. UWO is calculated as WO – EWO, where WO represents write-offs of uncollectible accounts per firms' Schedule II scaled by average total assets and EWO represents expected write-offs scaled by average total assets, obtained from the industry prediction model. To construct this figure, we calculate mean scaled bad debt expense, write-offs, expected write-offs, and unexpected write-offs by year.

FIGURE 2

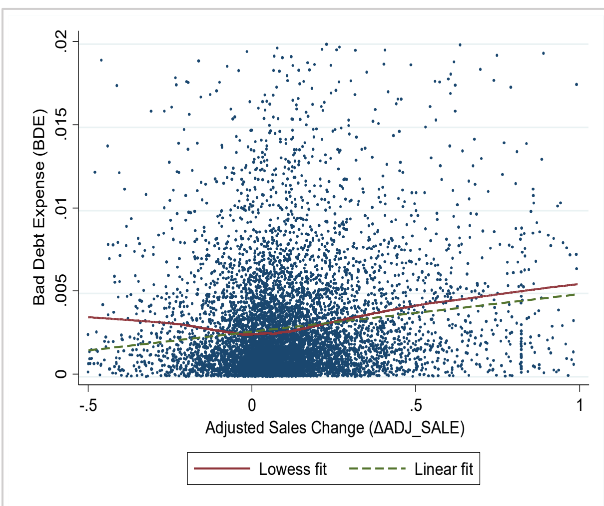
Scatterplots of Bad Debt Expense



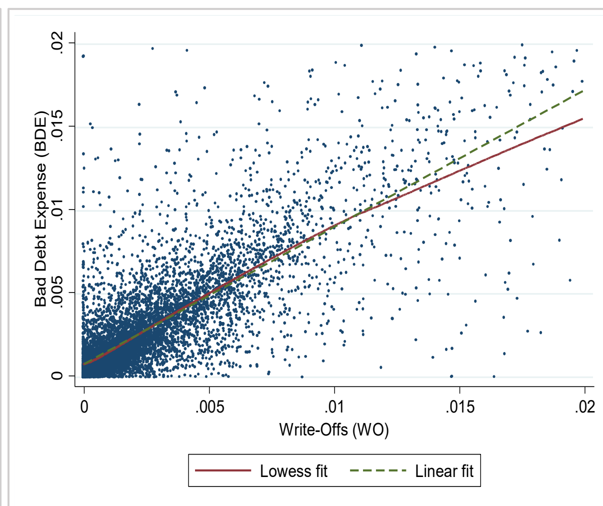
Panel A: BDE vs. ΔAR



Panel B: BDE vs. SALE



Panel C: BDE vs. ΔADJ_SALE



Panel D: BDE vs. WO

This figure presents scatterplots of bad debt expense (BDE) against the change in accounts receivable *(ΔAR)*, sales (SALE), the change in adjusted sales *(ΔADJ_SALE)*, and write-offs (*WO*) in Panels A – D, respectively. All variables are scaled by average total assets. The solid red line represents the locally weighted scatterplot smoothing (LOWESS) curve that non-parametrically depicts the relationship between the two variables. The dashed green line represents the OLS estimate for the same data.

FIGURE 3

Model Residuals and Changes in Accounts Receivable

Model 1: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \epsilon_t$

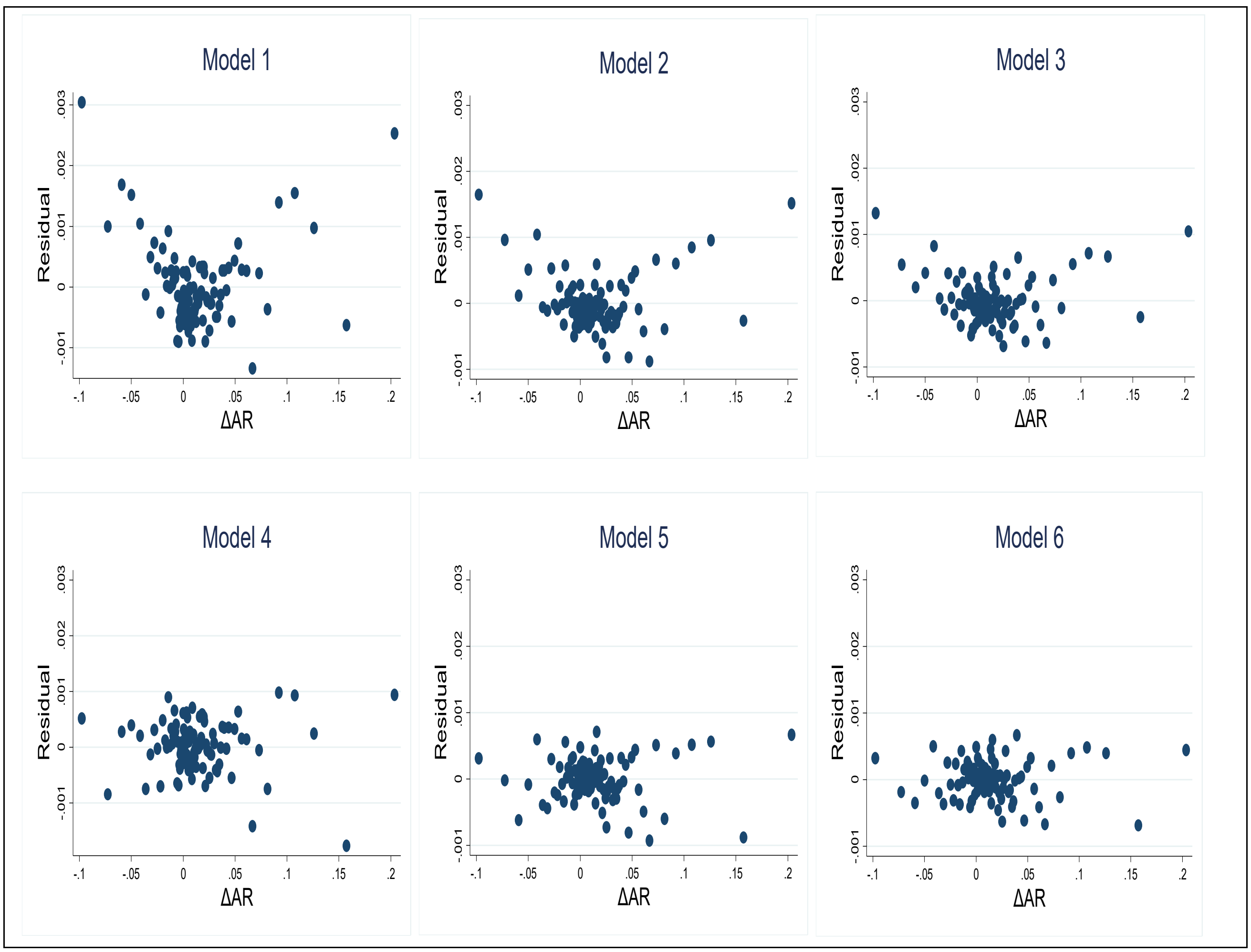
Model 2: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 WO_t + \epsilon_t$

Model 3: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 WO_t + \alpha_3 WO_{t+1} + \epsilon_t$

Model 4: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \ x \ \Delta AR_t + \epsilon_t$

Model 5: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \ x \ \Delta AR_t + \alpha_4 WO_t + \epsilon_t$

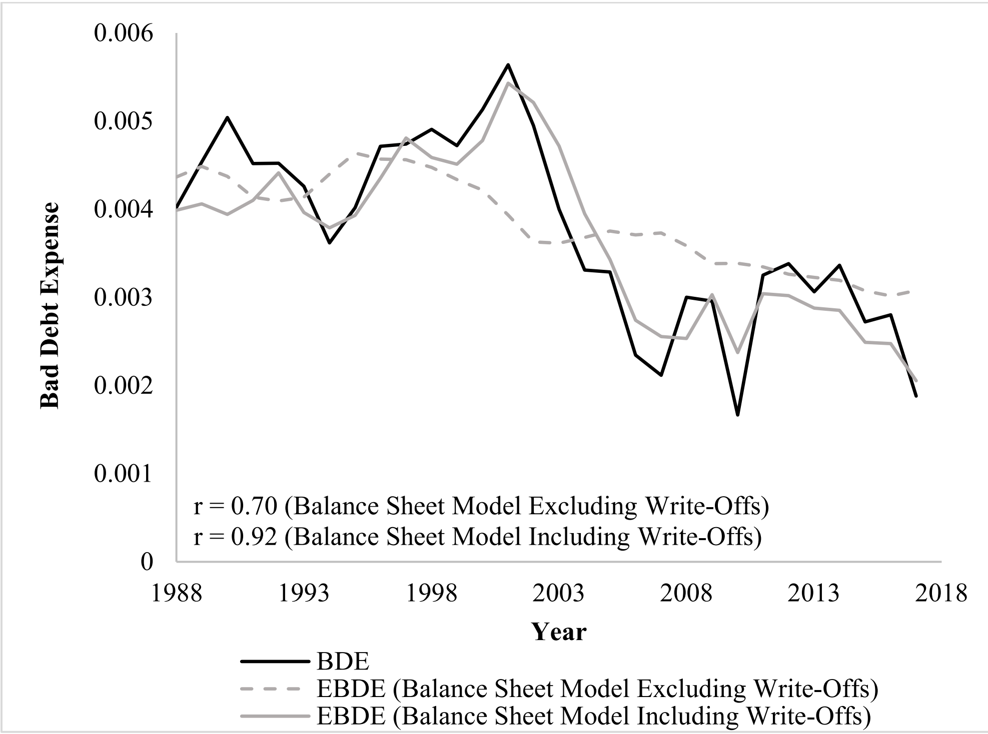
Model 6: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \ x \ \Delta AR_t + \alpha_4 WO_t + \alpha_5 WO_{t+1} + \epsilon_t$



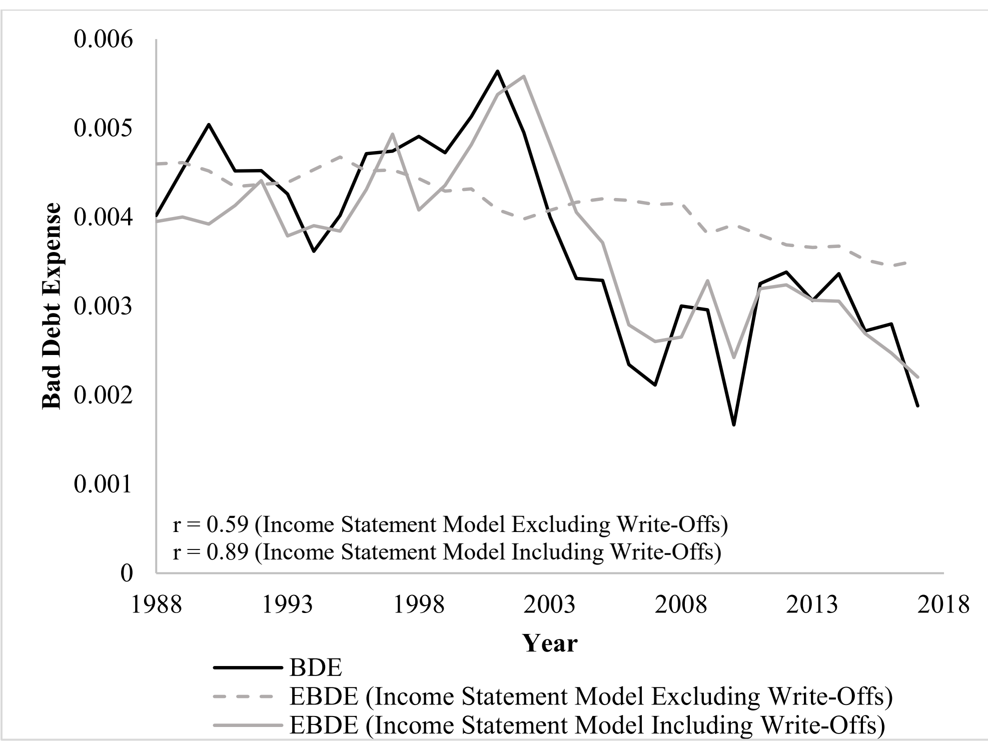
This figure plots the mean residuals from the six models in Table 2 against the mean ΔAR. Firm-year observations are divided into 100 equal frequency bins sorted on ΔAR, and the mean residuals from each of the models are plotted against the mean ΔAR in each bin.

FIGURE 4

Plots of Bad Debt Expense and Predicted Bad Debt Expense over Time



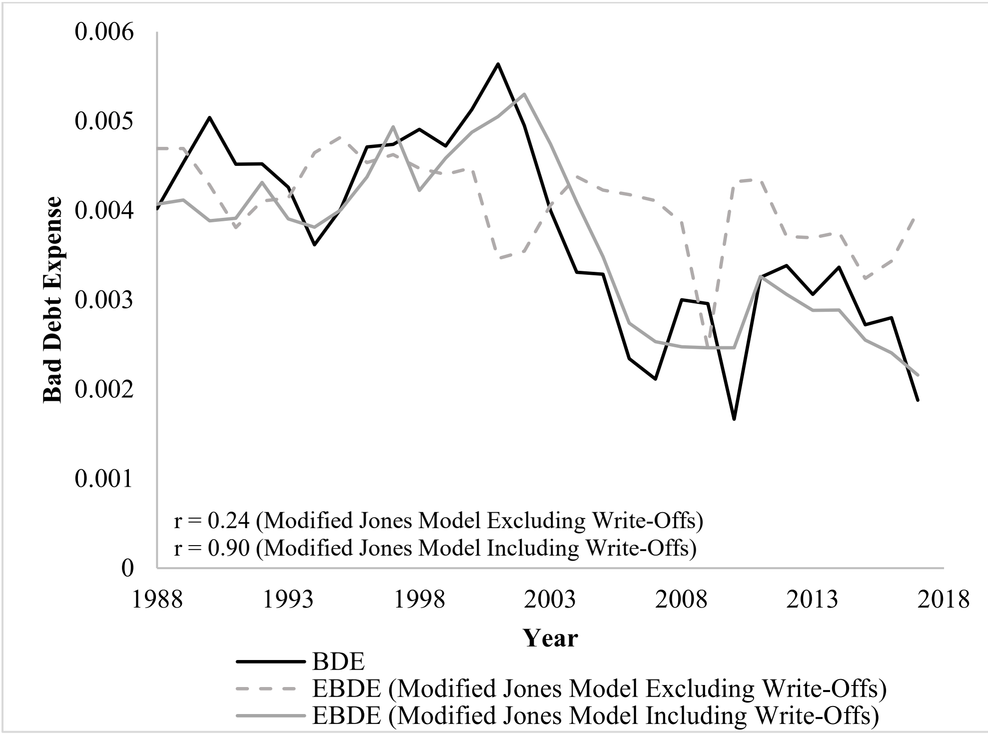
Panel A: Balance Sheet Models



Panel B: Income Statement Models

FIGURE 4, continued

Plots of Bad Debt Expense and Predicted Bad Debt Expense over Time

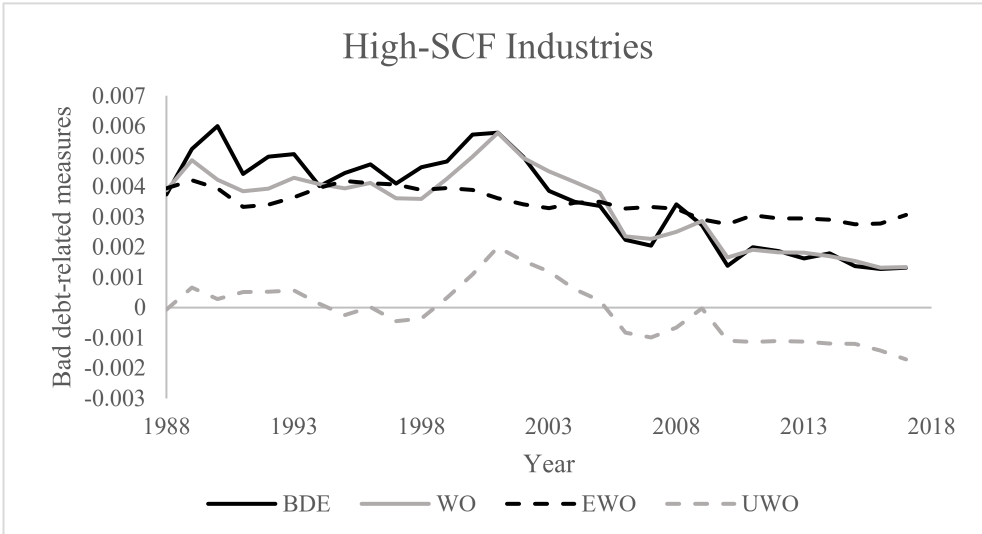


Panel C: Modified Jones Models

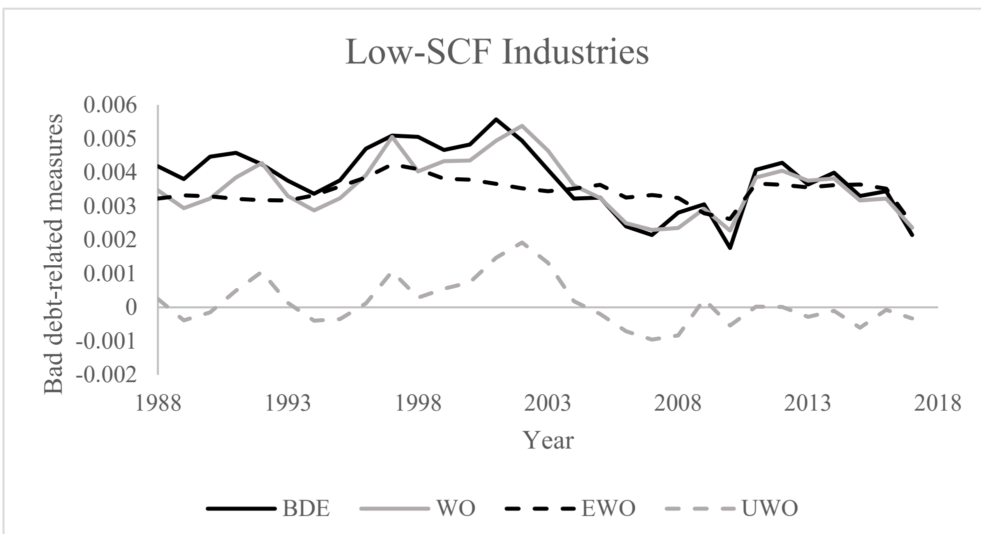
These figures plot the relationships between bad debt expense (BDE), expected bad debt expense (EBDE) and year for the sample period 1988 - 2017. All variables are scaled by average total assets. All panels report actual bad debt expense (BDE) which is obtained from firms' Schedule II. In Panel A, EBDE is obtained from the pooled prediction model using the balance sheet approach without write-offs and the balance sheet approach with write-offs. In Panel B, EBDE is obtained from the pooled prediction model using the income statement approach without write-offs and the income statement approach with write-offs. In Panel C, EBDE is obtained from the pooled prediction model using the modified Jones model without write-offs and the modified Jones model with write-offs. Correlation coefficients between bad debt expense and expected bad debt expense (i.e., r) are provided. To construct these figures, we calculate mean scaled bad debt expense and expected bad debt expense by year.

FIGURE 5

Plots of Bad Debt Expense and Write-offs over Time for High and Low SCF Industries



Panel A: High Supply Chain Finance Industries



Panel B: Low Supply Chain Finance Industries

These figures plot the relationships between bad debt expense (BDE), write-offs (WO), expected write-offs (EWO), unexpected write-offs (UWO) and year for the sample period 1988 - 2017. All variables are scaled by average total assets. In Panel A, we include firm-year observations from the following industries: consumer goods (SIC codes 20, 22, 23, 50, and 51), computer and office equipment (SIC code 3570), electronic computers (SIC code 3571), computer storage devices (SIC code 3572), computer terminals (SIC code 3575), computer communications equipment (SIC code 3576), computer peripheral equipment (SIC code 3577), manufacturing (SIC codes 25, 26, 27, and 39), and transportation equipment (SIC code 37). In Panel B, we include the rest of the sample. Bad debt expense and write-offs are obtained from firms' Schedule II. UWO is calculated as WO – EWO, where WO represents write-offs of uncollectible accounts per firms' Schedule II scaled by average total assets and EWO represents expected write-offs scaled by average total assets, obtained from the industry prediction model. To construct this figure, we calculate mean scaled bad debt expense, write-offs, expected write-offs, and unexpected write-offs by year.

TABLE 1

Summary Statistics

Panel A: Descriptive Statistics (N = 8,967)

	Mean	Std	p25	Median	p75
BDE_t	0.41%	0.90%	0.06%	0.16%	0.40%
ΔAR_t	1.43%	4.05%	-0.34%	0.82%	2.58%
WO_t	0.39%	0.88%	0.05%	0.15%	0.37%
WO_{t+1}	0.38%	0.86%	0.05%	0.14%	0.35%
$SALE_t$	133.06%	88.61%	79.40%	111.44%	157.25%
ΔADJ_SALE_t	11.52%	25.87%	-0.16%	7.89%	19.56%

Panel B: Pearson and Spearman Correlations

	BDE_t	ΔAR_t	WO_t	WO_{t+1}	$SALE_t$	ΔADJ_SALE_t
BDE_t		**0.156**	**0.763**	**0.754**	**0.320**	**0.162**
ΔAR_t	**0.211**		**0.062**	**0.080**	**0.216**	**0.640**
WO_t	**0.930**	**0.143**		**0.752**	**0.317**	**0.085**
WO_{t+1}	**0.898**	**0.177**	**0.878**		**0.310**	**0.096**
$SALE_t$	**0.116**	**0.237**	**0.219**	**0.205**		**0.375**
ΔADJ_SALE_t	**0.155**	**0.659**	**0.101**	**0.103**	**0.393**	

This table presents summary statistics for the variables used in the main regression analyses. The sample comprises 8,967 firm-year observations over the period 1988 to 2017. Panel A reports the descriptive statistics of the variables and Panel B reports the Pearson (Spearman) correlations between the variables below (above) the diagonal. Bold face indicates statistical significance at the 1% level in two-tailed tests. Variable definitions are in Appendix A.

TABLE 2

Model Comparison – Balance Sheet Approach

Model 1: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \epsilon_t$

Model 2: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 WO_t + \epsilon_t$

Model 3: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 WO_t + \alpha_3 WO_{t+1} + \epsilon_t$

Model 4: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \epsilon_t$

Model 5: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 WO_t + \epsilon_t$

Model 6: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 WO_t + \alpha_5 WO_{t+1}$

		Model					
		1	2	3	4	5	6
ΔAR_t	+	0.012***	0.015***	0.012***	0.030***	0.025***	0.019***
		(3.36)	(6.81)	(6.61)	(4.67)	(7.26)	(6.48)
$D\Delta AR_t$					0.000	0.000	-0.000
					(0.38)	(0.46)	(-0.08)
$D\Delta AR_t \times \Delta AR_t$	-				-0.060***	-0.032***	-0.024***
					(-5.66)	(-5.76)	(-4.85)
WO_t	+		0.766***	0.594***		0.760***	0.592***
			(16.06)	(13.02)		(15.86)	(12.93)
WO_{t+1}	+			0.322***			0.317***
				(8.54)			(8.37)
F-test*: $\Delta AR_t + D\Delta AR_t \times \Delta AR_t = 0$*					-0.030***	-0.007	-0.005
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2		0.734	0.891	0.910	0.739	0.893	0.910
Adj. within R^2		0.009	0.592	0.663	0.029	0.600	0.667

This table presents the results of estimating six models of bad debt expense as shown above and in section 3 of the main text. All models include firm fixed effects. The sample comprises 8,967 firm-year observations over the period 1988 to 2017. *t*-statistics are reported in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). See Appendix A for definitions of all variables in the regressions.

TABLE 3

Model Comparison – Income Statement Approach

Model 7: $BDE_t = \alpha_0 + \alpha_1 SALE_t + \epsilon_t$

Model 8: $BDE_t = \alpha_0 + \alpha_1 SALE_t + \alpha_2 WO_t + \epsilon_t$

Model 9: $BDE_t = \alpha_0 + \alpha_1 SALE_t + \alpha_2 WO_t + \alpha_3 WO_{t+1} + \epsilon_t$

Model 10: $BDE_t = \alpha_0 + \alpha_1 SALE_t + \alpha_2 D\Delta SALE_t + \alpha_3 D\Delta SALE_t \times SALE_t + \epsilon_t$

Model 11: $BDE_t = \alpha_0 + \alpha_1 SALE_t + \alpha_2 D\Delta SALE_t + \alpha_3 D\Delta SALE_t \times SALE_t + \alpha_4 WO_t + \epsilon_t$

Model 12: $BDE_t = \alpha_0 + \alpha_1 SALE_t + \alpha_2 D\Delta SALE_t + \alpha_3 D\Delta SALE_t \times SALE_t + \alpha_4 WO_t + \alpha_5 WO_{t+1} + \epsilon_t$

		Model					
		7	8	9	10	11	12
$SALE_t$	+	0.003***	0.001***	0.001***	0.003***	0.001***	0.001***
		(5.12)	(5.19)	(5.40)	(5.36)	(4.97)	(5.18)
$D\Delta SALE_t$					0.000	0.000	0.000
					(1.35)	(0.38)	(0.31)
$D\Delta SALE_t \times SALE_t$	-				0.000	-0.000	-0.000
					(0.71)	(-0.45)	(-0.79)
WO_t	+		0.752***	0.579***		0.752***	0.580***
			(15.02)	(12.39)		(15.02)	(12.43)
WO_{t+1}	+			0.328***			0.329***
				(8.62)			(8.64)
F-test: $SALE_t + D\Delta SALE_t \times SALE_t = 0$					0.003***	0.001***	0.001***
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2		0.741	0.889	0.908	0.741	0.888	0.908
Adj. within R^2		0.035	0.586	0.658	0.038	0.586	0.657

This table presents the results of estimating six models of bad debt expense as shown above and in section 3 of the main text. All models include firm fixed effects. The sample comprises 8,967 firm-year observations over the period 1988 to 2017. *t*-statistics are reported in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). See Appendix A for definitions of all variables in the regressions.

TABLE 4

Model Comparison – Modified Jones Model

Model 13: $BDE_t = \alpha_0 + \alpha_1 \Delta ADJ\_SALE_t + \epsilon_t$

Model 14: $BDE_t = \alpha_0 + \alpha_1 \Delta ADJ\_SALE_t + \alpha_2 WO_t + \epsilon_t$

Model 15: $BDE_t = \alpha_0 + \alpha_1 \Delta ADJ\_SALE_t + \alpha_2 WO_t + \alpha_3 WO_{t+1} + \epsilon_t$

Model 16: $BDE_t = \alpha_0 + \alpha_1 \Delta ADJ\_SALE_t + \alpha_2 D\Delta ADJ\_SALE_t + \alpha_3 D\Delta ADJ\_SALE_t \times \Delta ADJ\_SALE_t + \epsilon_t$

Model 17: $BDE_t = \alpha_0 + \alpha_1 \Delta ADJ\_SALE_t + \alpha_2 D\Delta ADJ\_SALE_t + \alpha_3 D\Delta ADJ\_SALE_t \times \Delta ADJ\_SALE_t + \alpha_4 WO_t + \epsilon_t$

Model 18: $BDE_t = \alpha_0 + \alpha_1 \Delta ADJ\_SALE_t + \alpha_2 D\Delta ADJ\_SALE_t + \alpha_3 D\Delta ADJ\_SALE_t \times \Delta ADJ\_SALE_t + \alpha_4 WO_t + \alpha_5 WO_{t+1} + \epsilon_t$

		Model					
		13	14	15	16	17	18
ΔADJ_SALE_t	+	0.002***	0.002***	0.002***	0.005***	0.003***	0.003***
		(3.77)	(6.51)	(6.77)	(4.72)	(7.04)	(7.31)
$D\Delta ADJ\_SALE_t$					0.001**	0.000*	0.000
					(2.16)	(1.65)	(1.42)
$D\Delta ADJ\_SALE_t \times \Delta ADJ\_SALE_t$	-				-0.007***	-0.004***	-0.004***
					(-4.53)	(-5.07)	(-5.29)
WO_t	+		0.763***	0.588***		0.757***	0.585***
			(15.82)	(12.86)		(15.68)	(12.81)
WO_{t+1}	+			0.328***			0.326***
				(8.62)			(8.58)
F-test: $\Delta ADJ\_SALE_t + D\Delta ADJ\_SALE_t \times \Delta ADJ\_SALE_t = 0$					-0.002***	-0.001	-0.001
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2		0.733	0.890	0.909	0.738	0.891	0.910
Adj. within R^2		0.011	0.591	0.662	0.026	0.596	0.664

This table presents the results of estimating six models of bad debt expense as shown above and in section 3 of the main text. All models include firm effects. The sample comprises 8,967 firm-year observations over the period 1988 to 2017. *t*-statistics are reported in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). See Appendix A for definitions of all variables in the regressions.

TABLE 5

The Effect of Expected and Unexpected Write-offs

Model 1: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \epsilon_t$

Model 2: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 EWO_t + \epsilon_t$

Model 3: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 EWO_t + \alpha_5 UWO_t + \epsilon_t$

Model 4: $BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 EWO_t + \alpha_5 UWO_t + \alpha_6 WO_{t+1} + \epsilon_t$

		Model			
		1	2	3	4
ΔAR_t	+	0.020***	0.015***	0.018***	0.014***
		(4.22)	(3.46)	(6.12)	(5.16)
$D\Delta AR_t$		-0.000	0.000	0.000	-0.000
		(-0.20)	(0.30)	(0.06)	(-0.43)
$D\Delta AR_t \times \Delta AR_t$	-	-0.045***	-0.035***	-0.022***	-0.016***
		(-5.67)	(-4.56)	(-4.46)	(-3.32)
EWO_t	+		0.908***	0.997***	0.776***
			(6.32)	(12.40)	(11.39)
UWO_t	+			0.775***	0.592***
				(11.62)	(10.37)
WO_{t+1}	+				0.358***
					(6.57)
F-test: $\Delta AR_t + D\Delta AR_t \times \Delta AR_t = 0$		-0.025***	-0.020***	-0.004	-0.002
Firm FE		Yes	Yes	Yes	Yes
Adj. R^2		0.734	0.746	0.866	0.891
Adj. within R^2		0.016	0.058	0.502	0.596

This table presents the results of estimating four models of bad debt expense as shown above and in section 3 of the main text. The variables EWO and UWO are obtained from the industry estimation model using OLS as discussed in the text. All models include firm fixed effects. The sample comprises 8,073 firm-year observations over the period 1988 to 2017. *t*-statistics are reported in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). See Appendix A for definitions of all variables in the regressions.

TABLE 6

Comparison of Bad Debt Expense for Firms in High and Low SCF Industries

Model 5: $$BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 D\Delta AR_t \times SCF_t + \alpha_5 SCF_t \times \Delta AR_t + \alpha_6 D\Delta AR_t \times \Delta AR_t \times SCF_t + \alpha_7 WO_t + \epsilon_t$$

Model 6: $$BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 D\Delta AR_t \times SCF_t + \alpha_5 SCF_t \times \Delta AR_t + \alpha_6 D\Delta AR_t \times \Delta AR_t \times SCF_t + \alpha_7 WO_t + \alpha_8 WO_{t+1} + \epsilon_t$$

Panel A: Full Sample Period

		Model	
		5	6
ΔAR_t	+	0.027***	0.022***
		(6.08)	(5.53)
$D\Delta AR_t$		0.000	0.000
		(0.68)	(0.13)
$D\Delta AR_t \times \Delta AR_t$	-	-0.035***	-0.026***
		(-4.64)	(-3.93)
$D\Delta AR_t \times SCF_t$		-0.000	-0.000
		(-0.67)	(-0.39)
$SCF_t \times \Delta AR_t$	0 or -	-0.009	-0.007
		(-1.43)	(-1.12)
$D\Delta AR_t \times \Delta AR_t \times SCF_t$	0 or +	0.009	0.007
		(0.93)	(0.82)
WO_t	+	0.759***	0.593***
		(15.92)	(12.97)
WO_{t+1}	+		0.317***
			(8.36)
Firm FE		Yes	Yes
Adj. R^2		0.893	0.910
Adj. within R^2		0.600	0.667

TABLE 6, continued

Comparison of Bad Debt Expense for Firms in High and Low SCF Industries

Panel B: Sample Partitioned Around Financial Crisis Period

		Model			
		Pre-2009		*Post-2008*	
		5	6	5	6
ΔAR_t	+	0.026***	0.022***	0.022***	0.016***
		(5.38)	(5.03)	(2.75)	(3.19)
$D\Delta AR_t$		0.000	0.000	-0.000	-0.000
		(1.12)	(0.71)	(-1.10)	(-1.54)
$D\Delta AR_t \times \Delta AR_t$	-	-0.029***	-0.022**	-0.042***	-0.034***
		(-2.87)	(-2.45)	(-3.57)	(-4.05)
$D\Delta AR_t \times SCF_t$		-0.000	-0.000	0.000	0.000
		(-0.91)	(-0.78)	(0.10)	(0.38)
$SCF_t \times \Delta AR_t$	Pre: 0	-0.007	-0.006	-0.017**	-0.012*
	Post: -	(-0.97)	(-0.84)	(-1.97)	(-1.72)
$D\Delta AR_t \times \Delta AR_t \times SCF_t$	Pre: 0	0.000	0.001	0.031***	0.023**
	Post: +	(0.01)	(0.06)	(2.61)	(2.27)
WO_t	+	0.714***	0.583***	0.724***	0.574***
		(13.57)	(11.29)	(11.36)	(6.94)
WO_{t+1}	+		0.298***		0.293***
			(6.93)		(3.87)
Firm FE		Yes	Yes	Yes	Yes
Adj. R^2		0.827	0.851	0.978	0.982
Adj. within R^2		0.525	0.592	0.625	0.692

This table presents the results of estimating two models of bad debt expense as shown above and in section 3 of the main text. All models include firm fixed effects. The variable *SCF* is omitted from the regressions because of collinearity with the firm fixed effects. Panel A consists of 8,967 firm-year observations over the period 1988 to 2017. In Panel B, the Pre-2009 subsample comprises 5,945 firm-year observations over the period 1988-2008 and the Post-2008 subsample comprise 3,022 firm-year observations over the period 2009 to 2017. *t*-statistics are reported in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). See Appendix A for definitions of all variables in the regressions.

TABLE 7

Comparison of Bad Debt Expense for High and Low SCF Firms

Model 5: $$BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 D\Delta AR_t \times HIGH\_SCF_t + \alpha_5 HIGH\_SCF_t \times \Delta AR_t + \alpha_6 D\Delta AR_t \times \Delta AR_t \times HIGH\_SCF_t + \alpha_7 WO_t + \epsilon_t$$

Model 6: $$BDE_t = \alpha_0 + \alpha_1 \Delta AR_t + \alpha_2 D\Delta AR_t + \alpha_3 D\Delta AR_t \times \Delta AR_t + \alpha_4 D\Delta AR_t \times HIGH\_SCF_t + \alpha_5 HIGH\_SCF_t \times \Delta AR_t + \alpha_6 D\Delta AR_t \times \Delta AR_t \times HIGH\_SCF_t + \alpha_7 WO_t + \alpha_8 WO_{t+1} + \epsilon_t$$

Panel A: Full Sample Period

		Model	
		5	6
ΔAR ΔAR_t	+	0.023***	0.018***
		(6.03)	(5.04)
$D\Delta AR_t$		0.000	0.000
		(0.66)	(0.07)
$D\Delta AR_t \times \Delta AR_t$	-	-0.027***	-0.020***
		(-4.29)	(-3.32)
$HIGH\_SCF_t$		0.001	0.001
		(1.49)	(1.35)
$D\Delta AR_t \times HIGH\_SCF_t$		-0.000	-0.000
		(-0.36)	(-0.45)
$HIGH\_SCF_t \times \Delta AR_t$	0 or -	-0.007	-0.009
		(-1.40)	(-1.37)
$D\Delta AR_t \times \Delta AR_t \times HIGH\_SCF_t$	0 or +	0.005	0.012
		(0.46)	(1.07)
WO_t	+	0.852***	0.632***
		(18.94)	(10.63)
WO_{t+1}	+		0.360***
			(6.23)
Firm FE		Yes	Yes
Adj. R^2		0.865	0.891
Adj. within R^2		0.665	0.730

TABLE 7, continued

Comparison of Bad Debt Expense for High and Low SCF Firms

Panel B: Sample Partitioned Around Financial Crisis Period

		Model			
		Pre-2009		*Post-2008*	
		5	6	5	6
ΔAR_t	+	0.023***	0.019***	0.007*	0.007**
		(5.49)	(4.69)	(1.95)	(2.04)
$D\Delta AR_t$		0.000	0.000	-0.000	-0.000
		(0.89)	(0.41)	(-1.28)	(-1.45)
$D\Delta AR_t \times \Delta AR_t$	-	-0.024**	-0.061*	-0.024***	-0.021***
		(-2.57)	(-1.94)	(-3.13)	(-3.07)
$HIGH\_SCF_t$		0.001	0.001	0.000	0.000
		(1.10)	(0.94)	(0.80)	(1.11)
$D\Delta AR_t \times HIGH\_SCF_t$		-0.000	-0.000	0.001	0.000
		(-0.50)	(-0.64)	(1.54)	(1.38)
$HIGH\_SCF_t \times \Delta AR_t$	Pre: 0	-0.009	-0.011	-0.009*	-0.009*
	Post: -	(-1.61)	(-1.42)	(-1.68)	(-1.94)
$D\Delta AR_t \times \Delta AR_t \times HIGH\_SCF_t$	Pre: 0	-0.001	0.007	0.062***	0.058***
	Post: +	(-0.10)	(0.48)	(7.28)	(6.94)
WO_t	+	0.803***	0.627***	0.812***	0.738***
		(16.18)	(10.08)	(8.39)	(6.34)
WO_{t+1}	+		0.352***		0.215**
			(5.58)		(2.53)
Firm FE		Yes	Yes	Yes	Yes
Adj. R^2		0.856	0.882	0.949	0.952
Adj. within R^2		0.573	0.650	0.593	0.622

This table presents the results of estimating two models of bad debt expense as shown above and in section 3 of the main text. All models include firm fixed effects. Panel A consists of 5,559 firm-year observations over the period 1988 to 2017. In Panel B, the Pre-2009 subsample comprises 4,083 firm-year observations over the period 1988-2008 and the Post-2008 subsample comprises 1,476 firm-year observations over the period 2009 to 2017. *t*-statistics are reported in parentheses based on standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). See the Appendix for definitions of all variables in the regressions.

TABLE 8

Tests of Earnings Management through Bad Debt Expense

Panel A: Specification Tests of Earnings Management through Bad Debt Expense – Full Sample

Model	Table, Model	Type I Error							Type II Error
		Full Sample	WO_t decile			ΔADJ_SALE_t decile			Full Sample
			Extreme Deciles	Top Decile	Bottom Decile	Extreme Deciles	Top Decile	Bottom Decile	
Modified Jones Model									
Excluding WO_t	4, 13	4.5	**66.2**	**96.9**	**72.2**	**22.6**	**13.4**	**47.6**	59.1
Including WO_t	4, 14	3.7	4.8	4.7	4.9	**22.5**	**10.3**	**48.3**	85.6
Including piece-wise linear structure	4, 16	4.3	**66.7**	**96.9**	**70.2**	5.0	3.9	3.8	59.6
Including piece-wise linear structure and WO_t	4, 17	3.1	4.8	4.6	5.8	4.7	3.7	4.6	85.3
Balance Sheet Model									
Excluding *WOt*	2, 1	4.4	**65.9**	**99.9**	**75.5**	**21.2**	**26.4**	**16.2**	59.2
Including *WOt*	2, 2	3.8	5.2	4.7	4.2	**19.5**	**20.1**	**20.8**	85.8
Including piece-wise linear structure	2, 4	4.6	**66.6**	**99.9**	**72.9**	**6.7**	**11.6**	2.7	59.7
Including piece-wise linear structure and WO_t	2, 5	3.8	5.7	4.4	4.9	**6.7**	**10.4**	4.7	86.5

TABLE 8, continued

Tests of Earnings Management through Bad Debt Expense

Panel B: Specification Tests of Earnings Management through Bad Debt Expense – Partitioned Sample

Subsample and Model	Table, Model	*Type I Error* Full Sample	*Type I Error* ΔADJ_SALE_t decile Extreme Deciles	*Type I Error* ΔADJ_SALE_t decile Top Decile	*Type I Error* ΔADJ_SALE_t decile Bottom Decile	*Type II Error* Full Sample
SCF =1 in Post-2008 Period						
Balance Sheet Model						
Excluding WO_t	2, 1	3.8	**15.1**	4.3	**11.4**	68.3
Including WO_t	2, 2	4.8	5.6	6.1	4.9	87.3
Including piece-wise linear structure	2, 4	4.8	5.2	5.6	4.3	68.9
Including piece-wise linear structure and WO_t	2, 5	5.2	5.7	6.1	4.9	87.0
Rest of Sample						
Balance Sheet Model						
Excluding *WOt*	2, 1	4.0	**18.8**	**22.0**	**16.8**	55.6
Including *WOt*	2, 2	3.0	**9.6**	**10.4**	**14.1**	81.2
Including piece-wise linear structure	2, 4	5.0	5.0	6.1	3.2	56.6
Including piece-wise linear structure and WO_t	2, 5	4.3	4.9	5.3	4.9	82.2

This table reports tests of earnings management through bad debt expense (*BDE*). Panel A reports the simulation results for Type I and Type II errors for the full sample. For Type I error, we simulate for both the modified Jones and the balance sheet models. We randomly draw 100 firm-year observations (representing 1.1% of total observations) from the full sample, or the extreme deciles, top decile, or bottom decile of firm-years ranked by *WO* or *ΔADJ_SALE*. We create an indicator *PART* that equals 1 for these observations (0 otherwise). We report the percentage of significant coefficient on *PART* at the 5% level from 1000 simulations. Rejection rates that are significantly above the nominal significance level (above 6.3%) are in bold. For Type II error, we randomly select 1.1% of firm-years from the full sample and subtract 10% of the standard deviation of *BDE* from actual *BDE* to obtain seeded discretionary bad debt expense. We set *PART* equal to 1 for these observations (0 otherwise). We report the percentage of significant coefficient on *PART* at the 5% level using a one-tailed *t*-test. In Panel B, we conduct similar analyses but for two subsamples: firms in the SCF industry in the post-2008 period and the rest of sample. See Appendix A for definitions of all variables.