Do cash flows predict loan losses earlier than accruals?

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Abstract

The debate over when loan losses should be recognized is among the most durable in banking. Yet empirical research on recognition timing has relied almost entirely on accrual-based measures produced by the creditor. Using commercial mortgage-backed securities, where the underlying borrower payment record is observable, we compare borrower payment shortfalls with the creditor's reported delinquency classification as predictors of loss recognition. The delinquency classification predicts write-downs over the following year, while borrower payment shortfalls remain predictive at longer horizons, with evidence extending into the fourth year. Prior payment shortfalls also predict subsequent recognition after a loan has returned to current status and carries no recent delinquency classification. Our findings suggest that accruals can sharpen information close to recognition without fully preserving the information contained in underlying cash flows, and identify borrower-level payment information as a potentially useful cash-flow disclosure for financial institutions.

Keywords Loss recognition · Cash flows · Accruals · Credit risk · CECL · CMBS

JEL Classification G21 · G23 · M41 · M48 · R33

1 Introduction

When a loan loss should be recognized is among the most durable questions in financial reporting. Loans are the largest asset of many financial institutions and credit losses are among their largest expenses, so the timing of recognition affects reported earnings, regulatory capital, and the capacity to extend new credit. The problem is especially important in downturns, when deterioration across many loans can become visible at once and recognition occurs precisely when capital is most valuable. A long literature therefore asks whether creditors recognize losses in a timely manner and what happens when they do not (Beatty and Liao 2011; Vyas 2011; Bushman and Williams 2015). At its core, that literature asks when deterioration becomes visible relative to when the accounting system records it.

Yet empirical research on this question has relied almost entirely on measures that themselves depend on the judgment of the creditor. Researchers observe loan-loss provisions, allowances, nonperforming classifications, and charge-offs (Wahlen 1994; Beaver and Engel 1996; Ahmed et al. 1999; Nichols et al. 2009; Beatty and Liao 2011). These measures are informative because creditors process information unavailable to outsiders. But they also make recognition timing difficult to evaluate: the benchmark used to assess timeliness is itself produced through the reporting process whose timing is under study. The one input the creditor does not determine is whether the borrower made the contractual payment.

That input is usually unavailable to researchers. Call Reports disclose past-due balances by loan category rather than the payment that was missed, and even loan-level regulatory collections generally do not provide a comparable monthly borrower-payment record (FFIEC 2024; Board of Governors 2024). Cash flows have long provided a benchmark for evaluating accrual-based measures outside financial institutions (Dechow 1994; Sloan 1996), but that

comparison has been difficult to make for loan losses because the relevant cash flow cannot normally be observed. We ask whether the borrower's payment record predicts subsequent loss recognition earlier than the delinquency classification assigned to the same loan.

We answer the question in U.S. commercial mortgage-backed securities, where the borrower's payment record is publicly observable. When a scheduled payment does not arrive, the pooling and servicing agreement requires the master servicer to advance principal and interest, and the monthly filing reports the resulting advance balance. We use these advances to identify borrower payment shortfalls and compare them with the delinquency classification reported for the same loan in the same filing.[1] The subsequent appraisal-reduction write-down provides the recognition event. The setting therefore lets us observe three points in the same deterioration process separately: borrower nonpayment, creditor classification, and subsequent loss recognition.

CMBS is useful for this question for three reasons. First, borrower payment shortfalls are observable monthly and loan by loan, whereas comparable information is ordinarily unavailable to outside users of bank financial statements. Second, the institution that originated the loan is separate from the parties that subsequently service the loan and recognize the loss, so the timing we observe cannot simply reflect an originating lender protecting its own underwriting decision. Third, the setting gives the formal classification a relatively favorable test: servicing agreements impose explicit delinquency rules, and delinquency and transfer to special servicing are themselves connected to the appraisal process underlying the write-down. These features do not make CMBS identical to a bank

[1] We do not tune a threshold, weight several disclosures into a composite, or require the advance to persist, so that whatever the measure predicts is not an artifact of a choice we made. Section 5.4 varies the construction and shows that the estimate strengthens when persistence is required.

portfolio, and we do not interpret the precise horizons we estimate as bank estimates. They instead provide a comparatively disciplined setting in which to ask whether the underlying payment record contains information beyond the creditor's reported classification.

We find that it does. The delinquency classification predicts write-downs primarily over the following year, while borrower payment shortfalls remain predictive at longer horizons, with evidence extending into the fourth year. The difference is not that cash flows dominate classification everywhere. Classification is most informative close to recognition, consistent with judgment and additional creditor information sharpening the measure as deterioration persists. The payment record instead reaches further back into the deterioration process.

A second result shows that the longer horizon is not merely the first stage of a delinquency episode that eventually appears in the classification. We examine loans that are currently paying and carry no recent delinquency classification. Prior payment shortfalls continue to predict subsequent write-downs. The current classification therefore does not fully preserve the information contained in the borrower's payment history.

The results are robust to alternative constructions of borrower payment shortfalls, stricter delinquency thresholds, controls for property fundamentals, alternative risk sets and sample definitions, and additional fixed effects. Requiring payment problems to persist and distinguishing new advances from increases in existing advances produces the same broad conclusion. The evidence is strongest over the first several years and weakens at the furthest horizon. We therefore interpret the findings as evidence about the timing and preservation of information, not as evidence that a missed payment is itself an unrecognized loss.

The findings also speak to an active question about cash-flow reporting by financial institutions. In 2023, the FASB began reconsidering the statement of cash flows for financial

institutions after hearing that some users were “not using the statement in certain industries.” The Board discontinued the institution-specific project in April 2026 but folded the issue into its broader reconsideration of cash-flow reporting (FASB 2023, 2026). Our evidence speaks to the question beneath that project: which cash flows are useful for evaluating financial institutions? Borrower payment performance is one candidate because it contains information about subsequent loss recognition that the contemporaneous credit classification does not fully retain.

This study makes three contributions. First, it contributes to the literature on the timeliness of loan-loss recognition. That literature establishes timeliness using provisions, allowances, nonperforming loans, and charge-offs and relates delayed recognition to lending, risk, and financial stability (Beatty and Liao 2011; Vyas 2011; Bushman and Williams 2015). We introduce a borrower-side benchmark that becomes observable when contractual cash is not received rather than when the creditor changes a reported credit state. The results show that the horizon over which borrower payment information remains informative exceeds the horizon over which the current delinquency classification carries positive incremental information.

Second, the paper contributes to the literature on accruals and cash flows. Accrual-based measures can improve on cash by processing information, correcting timing differences, and incorporating expectations about future outcomes (Dechow 1994; Dechow and Dichev 2002; Ball and Nikolaev 2022). We show that this advantage can vary with the horizon. The creditor’s classification is substantially more informative close to recognition, but the underlying cash record retains information at longer horizons and after the loan has returned

to a current reported state. Thus, judgment can sharpen a measure near the outcome without fully preserving the information contained in the underlying cash-flow history.

Third, the paper contributes to the debate over financial-institution disclosure. The usual statement of cash flows was not designed around an institution whose assets themselves generate financing cash flows, and recent standard-setting activity reflects uncertainty about what cash-flow information is useful in that setting. We identify borrower payment performance as one such source of information. We do not argue that it should replace creditor judgment or determine when losses are recognized. Rather, borrower-level payment information can complement existing credit classifications and represents a potentially useful cash-flow disclosure for financial institutions.

Two caveats bound these conclusions. The design establishes information and timing, not intentional delay, and it does not imply that a loss should be recognized when the first payment shortfall appears. Nor do the exact magnitudes or horizons necessarily generalize from CMBS to bank portfolios, where creditors have different information, modification authority, and control over workouts. The narrower conclusion is that borrower cash flows can contain information before formal classification and can retain information that the current classification no longer displays.

The rest of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 reviews the related literature and develops the hypothesis. Section 4 describes the sample, the variables and the research design. Section 5 reports the results. Section 6 concludes.

2 Institutional setting: commercial mortgage-backed securities

2.1 The trust, the parties and the monthly record

A loan held in a commercial mortgage-backed securities trust generates three records of the same deterioration, in the same monthly reporting cycle, produced under different rules and by different parties. Under Regulation AB II, SEC-registered trusts have filed a standardized asset-level schedule for every loan each month since November 2016. The schedule reports whether the master servicer is advancing its own funds because the scheduled borrower payment did not arrive, and separately how many days past due the same loan is. The trust's own recognition event, an appraisal reduction, is dated in the accompanying Form 10-D.

The loan is originated by a bank or a conduit lender and sold into the trust, so the institution that recognizes the loss is not the institution that made it. The master servicer is "responsible for the day to day administration of the loans," and among its duties it "monitors and manages delinquencies, and provides liquidity to a transaction by advancing principal and interest on delinquent loans" (Trepp and Savitsky 1999, p. 110). The special servicer is engaged once a loan is seriously troubled and holds the powers to extend, modify, restructure or foreclose on it (Dunlevy 1999, p. 120).

One firm therefore produces the payment record and the classification for the same loan in the same month, and neither is produced by the lender that underwrote it. The three records are the borrower's payment shortfall, the creditor's delinquency classification and the appraisal-reduction write-down, and we take them in turn, with the property measures a portfolio lender would use in their place. Appendix B follows one loan through all three.

2.2 Borrower payment shortfalls and the servicer advance

The servicing contract makes borrower nonreceipt observable through the mandatory advance. The filed field is the outstanding balance of those advances rather than the amount advanced in the month, so a positive value indicates an outstanding servicer advance generated by borrower nonpayment. Section 5.4 separately identifies the month in which the balance moves from zero to positive and the months in which it rises. When a scheduled payment does not arrive, the pooling and servicing agreement obliges the master servicer to advance the principal and interest out of its own funds so that certificateholders are paid on schedule. The advance obligation is determined by nonreceipt on the monthly payment cycle and attaches no grace period, no delinquency threshold and no forecast of eventual loss. Contemporaneous descriptions state the rule in the same terms: the servicer “will advance both principal and interest,” and “advancing will continue from the servicer for as long as these amounts are deemed recoverable” (Dunlevy 1999, p. 115).

The advance is a loan to the trust rather than a cost the servicer bears. It is reimbursed with interest and sits at the top of the waterfall, so the servicer’s exposure is a funding position rather than a credit position, and the average amount outstanding in our panel is five basis points of the loan balance. Making the advance does not itself constitute loss recognition or an assessment that the loan is impaired. It meets an obligation written before the loan deteriorated.

A key exception to the advance obligation is recoverability. No party must advance an amount it determines will not ultimately be recovered from the loan or the property. That determination arrives late in a loan’s life rather than at the onset of nonpayment. This

discretion can cause SHORTFALL to return to zero late in a loan's deterioration and therefore can generate false negatives.

A second limitation is maturity default. Servicers "do not advance a balloon payment, but are required to advance interest and scheduled principal payments through foreclosure" (Jacob et al. 1999, p. 298), so a borrower who reaches maturity unable to repay principal while meeting monthly installments generates no advance. Balloon loans default at materially higher rates than fully amortizing loans, and most of those defaults occur at the balloon date rather than during the term (Pelletier and Rudenstein 1999, pp. 65–66). We report the maturity-status codes descriptively rather than folding them into SHORTFALL.

2.3 The delinquency classification

The delinquency classification is a creditor-produced summary of the loan's reported payment status rather than an observation of whether the scheduled payment arrived. It is the intermediate classification between borrower nonpayment and the accounting recognition event, and it is the measure the bank literature uses as its nonperforming analogue.

Four features of the classification matter for what follows. It is the standard analogue in this literature to the nonperforming status a bank reports. The servicer assigns it from the operative schedule rather than observing whether cash arrived. Grace, forbearance and modification can withhold it or reset it. And it is the creditor-produced measure closest to recognition, since an uncured sixty-day delinquency is itself among the events that require the new appraisal on which the write-down rests.

The payment-status field is reported on a standardized legend (CRE Finance Council 2015). The day count is arithmetic conditional on the operative payment schedule, once the date through which the loan is paid falls a given number of days behind the date the payment

was due, and judgment enters through grace, forbearance, modification and schedule resets, and at thirty, sixty and ninety days past due it moves through progressively stricter thresholds.

Below thirty days the legend carries a grace-period code, defined as a payment not received but still within the grace period or not yet due, and a late-payment code for a payment less than thirty days delinquent. It carries separate codes for loans that have passed maturity while still paying and for loans that have passed maturity and stopped. On all four the thirty-day indicator equals zero by construction. Codes A and B form the mild-status subsample used in Section 5.4; codes 4 and 5 capture maturity status and are reported separately.

We use the thirty-day threshold in the main specifications. It is the earliest available conventional delinquency benchmark reported in this market and the closest analogue to the nonperforming measures the bank literature uses.

Three features of the legend limit what the classification records. A loan inside its grace period is behind on its payment and is not delinquent. A loan under a forbearance agreement is meeting the schedule that agreement set, and is reported current while no cash arrives. And a modified loan is measured against its new schedule, so a loan ninety days behind its original obligation can be reported current in the month the modification closes.

Market participants use several conventional delinquency thresholds rather than one. Within a single industry volume, definitions of default range from sixty days past due on debt service to ninety days or more (Pelletier and Rudenstein 1999, p. 54; Dunlevy 1999, p. 120; Corcoran and Kao 1999, p. 254). That variation motivates the sixty-day and ninety-day tests in Section 5.4.

2.4 The write-down

The recognition event we predict is the appraisal reduction. When the collateral is reappraised below what the trust is owed, the trust records the reduction, cuts the interest advanced to the most junior certificates, and notionally reduces certificate balances for allocating control rights. Realized losses are allocated only when the property is sold, so the appraisal reduction is the trust's estimate of a loss it has not yet taken.

The device was described in those terms at the market's outset. Its purpose is "to anticipate losses by requiring an updated appraisal on any property where certain criteria are met (such as a specified level of delinquent loan payments)," and "to recognize the anticipated loss (similar to marking-to-market losses) and thereby promptly reduce the first-loss position" (Trepp and Savitsky 1999, p. 102). It is the closest analogue in this market to a specific allowance in a bank: an anticipatory estimate against an identified loan, recorded before any cash loss. The delinquency classification is the intermediate creditor classification; the appraisal reduction is the accounting recognition event.

Two features carry into our design. The first is that a new appraisal is required by specified credit events, including an uncured sixty-day delinquency and transfer to special servicing (Carlson 2026). This mechanical link should strengthen the association between delinquency and the write-down.

2.5 Generalizability

We chose this setting because the borrower payment record is publicly observable in it, which is not the normal case. CMBS trusts differ from bank portfolios in ways that affect the external validity of the estimates, and we distinguish between institutional features likely to generalize and the magnitudes estimated here.

In a bank the same missed payment produces a single record, and the bank itself produces it. No third party advances the shortfall, so the missed payment leaves no trace outside the bank's loan system other than the classification the bank assigns. That classification reaches the public through the Call Report, quarterly, by loan category and as a balance rather than a missed payment, and the reporting convention is partly the bank's to elect (FFIEC 2024). Even the Federal Reserve's loan-level collection for the largest banks reports days past due at quarter end, censored below thirty, and carries no payment field (Board of Governors 2024).

The difference between the two settings that matters most is renegotiation. A bank holding a commercial mortgage is usually the sole creditor and faces few restrictions on modifying the loan, while a trust cannot do the same: the pooling and servicing agreement and the tax rules that exempt the trust together require the loan to be transferred to the special servicer before it is modified (Internal Revenue Service 2009; McQueen et al. 2013; Flynn et al. 2024). The consequence is visible in the one study that observes both channels at the loan level. Among distressed loans, those in CMBS are mostly delinquent while those in bank portfolios are mostly modified (Glancy et al. 2022b; see also Black et al. 2017).

The difference operates in two directions. In a bank a missed payment can be cured by a modification before it is ever classified, and a modified loan that meets its new schedule is reported current, so the bank's classification forms later, on fewer of the loans that missed a payment, and after the bank has decided what to do with the loan. These institutional differences could make the corresponding interval wider in bank portfolios, but the CMBS design does not identify its magnitude. A second difference may strengthen the predictive content of bank classifications: because a bank decides both the classification and the

workout, its classification is partly a forecast of its own intended action. That channel may increase near-term predictive content, but it does not change the chronological ordering of payment nonreceipt and subsequent classification.

The magnitudes estimated in CMBS need not generalize to bank portfolios because the underlying loan populations differ substantially in size, rate structure, leverage and property mix, and because banks hold roughly four times the securitized share of the commercial mortgage market (Glancy et al. 2022a). We therefore make no claim about how many months the interval would run inside a bank, on which loans, or at which horizons the relative predictive coefficients would differ. The institutional comparison suggests that borrower payment information can precede creditor classifications in bank portfolios as well, but the CMBS evidence does not directly test that setting.

3 Related literature and hypothesis development

3.1 Related literature

Research on the extent to which the creditor's classification lags the payment record it summarizes is limited. Most studies in the accounting literature evaluate the timeliness and validity of provisions and allowances by relating them to other creditor-produced measures (e.g., Ballew and Sheneman 2025; Bischof and Rudolf 2025). Bischof and Rudolf (2025) ask whether managerial discretion makes provisions more or less timely. We ask whether the benchmark against which that timeliness is measured itself reflects delayed recognition. Provisions respond to capital pressure, earnings targets, ownership and policy uncertainty as well as to credit (Moyer 1990; Ahmed et al. 1999; Liu and Ryan 2006; Nichols et al. 2009; Ng et al. 2020), and the resulting delay carries consequences: banks that recognize expected losses late lend less when capital becomes scarce and carry more tail risk (Beatty and Liao

2011; Bushman and Williams 2015), and wrote down assets less promptly during the financial crisis where leverage and regulatory constraints were binding (Vyas 2011). Beatty and Liao (2014) survey the field. Although these studies examine the timeliness of the creditor's recognized numbers, they do not consider how far ahead of those numbers the borrower payment record is observable, because the nonperforming classification and the charge-off are themselves creditor-assigned states.

The passage of the expected loss standards has increased interest in estimating credit deterioration from public disclosures. Harris et al. (2018) develop a measure of the one-year-ahead expected rate of credit losses and show that it predicts charge-offs incremental to current charge-offs, allowances, provisions and loan fair values. Wheeler (2021) develops a measure of lifetime expected losses using vintage analysis and shows that share prices reflect the difference between that measure and the recorded allowance. Both papers construct an estimate the creditor does not report and evaluate the reported number against it. Our approach is conceptually similar, in that we also evaluate a reported credit measure against a benchmark generated by a contractual servicing obligation rather than by the delinquency-classification decision. Both construct an estimate of expected losses. Our benchmark is instead an observed borrower payment event, used to evaluate a creditor-produced classification.

Our paper also relates to work using mandated asset-level reporting to study behavior that is otherwise invisible. Neilson et al. (2022) show that the Regulation AB II regime changed how asset-backed securities are valued and provide the data architecture we follow; loan-level mandates elsewhere improved loan quality and harmonized standards within banks (Ertan et al. 2017; Kang et al. 2021), at a cost (Nicoletti and Zhu 2023). A related line shows

that what is reported to a trust is itself managed (Dietrich et al. 2000; Kruger and Maturana 2021; Griffin and Priest 2023). The servicer advance has also been used in prior work. Aiello (2022) constructs the same loan-level advance in residential securitizations to study servicer liquidity and instruments for the credit-information component that is central to our analysis. Chen and Deng (2013) show that property cash flow conditions drive the special servicer's workout decision, using the property's annual borrower-reported income rather than a monthly record of whether the installment arrived. Flynn et al. (2024) show that borrowers solicit transfers to special servicing strategically, which is why our recognition event is the appraisal reduction rather than the transfer.

3.2 Hypothesis development

A prediction that the classification is the better predictor of an impending loss assumes that the two are independent readings of the loan. The two measures are not independent because the delinquency classification is formed partly from the underlying payment history: it is raised because payment stopped and then timed, withheld or reset by grace, forbearance and modification. The delinquency classification is not an accrual. It is a creditor-produced credit classification, and the appraisal reduction is the accounting recognition event. The classification is not forecasting cash not yet received; it is largely a processed reading of a payment failure that has already occurred, and a classification built on its own input improves on that input only where the thresholding and the additional information embedded in the classification add something. The question is therefore whether the classification still predicts recognition once the current SHORTFALL indicator is held fixed. A definitional ordering between the two records does not by itself imply a predictive gap, since a state produced

through a threshold and a waiting period can correlate almost perfectly with the state that produced it (Löffler 2004).

The two measures should not dominate at the same distance from the event. The advance obligation arises when the payment is missed, so an outstanding advance can reveal the payment problem before the thirty-day classification, and it is also the noisier measure: borrowers cure, and a shortfall in a single month is a weak statement about whether the loan will be lost. The classification records that the shortfall has persisted past an institutional threshold. It is observed later but should have greater near-term predictive content because the payment problem has persisted beyond the classification threshold, and because by then many loans on which it has not formed have cured. At longer horizons, SHORTFALL may vary across loans before DELINQUENT 30+ has been recorded.

Two explanations of the classification remain within that framing, and they imply different coefficient patterns when both measures enter the regression. Under the first, the classification adds information through persistence, the contractual threshold and the servicing status against which delinquency is measured, so it carries content the payment record does not and retains its coefficient once the payment record is held fixed (Wahlen 1994; Beaver and Engel 1996). Under the second, it largely re-records the same payment failure with a lag, so the payment record retains predictive content at the horizons at which the classification has not yet formed. They differ in the horizons over which each measure carries incremental information when both are included.

Approximately one month of the interval is mechanical: the advance obligation arises when payment is missed, whereas DELINQUENT 30+ requires the loan to cross the thirty-day threshold. Larger differences can arise from cures, repeated shortfall episodes,

modifications and other servicing states. The prediction concerns the horizon over which each measure carries information rather than which measure is better overall. The classification should be more informative near recognition, because by then persistence past the threshold has been established. The question is whether the payment record retains incremental predictive content over horizons at which the classification no longer does, and whether a payment shortfall the classification never recorded remains informative once the loan is reported clean again.

> H1: Borrower payment shortfalls contain information about subsequent loss recognition beyond the delinquency classification the creditor reports, at horizons over which the classification has little incremental predictive content and after the loan has returned to current status with no recent classification.

4 Data, variables and research design

4.1 Variables

We measure borrower payment shortfalls from the servicer advance. SHORTFALL(i,t) equals one when loan i carries a positive outstanding principal-and-interest advance balance in month t, and zero otherwise. The field is a stock as of the reporting date rather than the amount advanced in the month, so a positive value indicates an outstanding servicer advance generated by borrower nonpayment. Because a balance can persist after the month in which it was created, Table 5 separately identifies zero-to-positive onsets and increases in the balance. The obligation that produces the field is written into the pooling and servicing agreement before the loan deteriorates, is owed in the month the installment is not received, and requires no forecast of eventual loss, which is what makes the field usable as a record of borrower

payment trouble rather than as a servicer credit assessment. The measure is deliberately simple. We use the indicator as the filings report it rather than tuning a threshold or a persistence window to maximize prediction, and the one persistence variant we report is a robustness test rather than a specification choice. The object of interest is whether the borrower cash shortfall is present rather than the size of the servicer's temporary funding position, so we do not use the size of the advance as a predictor.

A one on this measure is a strong indication that the scheduled borrower payment was not received. A zero is less definitive, for the two measurement limitations set out in Section 2.2. A servicer can stop advancing after determining that an advance would not be recoverable, which censors the measure from above late in a loan's life. And a borrower can reach maturity without repaying principal while continuing to make monthly installments, which produces no advance at all. The latter case is visible in the payment-status field as a performing-matured loan. Table 1 Panel A and Table 2 Panel B report the maturity-status codes descriptively, and the 399 loan-months carrying codes 4 and 5 remain in the estimation panel, where DELINQUENT 30+ equals zero for them by construction. This is a limitation of SHORTFALL rather than a separate state in the model.

More generally, the indicator says nothing about the depth of delinquency and is recorded by the servicer rather than observed from the borrower's account. Advance behavior is also not perfectly mechanical: affiliated servicers have been shown to advance more than a disinterested agent would (D'Lima and Lopez 2021), and non-recoverability determinations and curtailments censor the measure (Kroll Bond Rating Agency 2025). These features introduce measurement error and heterogeneity in SHORTFALL. We address persistent differences in servicer reporting practices in specifications with servicer fixed effects.

We measure the classification side with the reported payment status, described in Section 2.3. DELINQUENT 30+(i,t) equals one if the servicer reports loan i as thirty or more days past due in month t, and zero otherwise, with DELINQUENT 60+(i,t) and DELINQUENT 90+(i,t) defined analogously at the stricter thresholds. The thirty-day threshold is the earliest conventional delinquency classification reported in this market and the closest analogue to the nonperforming measures the bank literature uses.

The two measures are closely related but not identical, so the main regressions enter them jointly rather than separately, and each coefficient captures the incremental association conditional on the other. Because nearly every classified loan-month also records an outstanding advance, the classification coefficient is identified largely from loan-months that carry both. Section 5.5 reports a decomposition into mutually exclusive current combinations as a check on that reading.

DSCR < 1(i,t), a debt-service coverage ratio (DSCR) below one, and OCCUPANCY < 80%(i,t), physical occupancy below 80%, measure the collateral rather than the borrower's payment record, and they are the measures a portfolio lender would have. Their limitation is the numerator. The definition of net operating income is itself contested, with "over a dozen definitions of how to calculate an NOI" in use (Trepp and Savitsky 1999, p. 97), and the figure is stale: commercial real estate performance reporting is on average four quarters old, only about a quarter of loans report financial statements in a given quarter, and additional staleness is associated with higher default risk (Hughes and Nichols 2025). A coverage ratio can therefore read comfortably above one in the month a borrower stops paying. We exclude the loan-to-value ratio because the filed value is updated selectively after origination and can therefore reflect servicing actions taken after deterioration begins (Ervolini et al. 1999, p.

267); prior work also reports a weak relationship between loan-to-value and default in this asset class (Archer et al. 2002).

4.2 Sample and descriptive statistics

We begin with the asset-level schedules filed on Form ABS-EE by SEC-registered CMBS trusts subject to Regulation AB II from November 2016, the first month of asset-level reporting, through December 2025. We restrict the sample to SEC-registered deals because privately placed 144A deals do not file the same schedules. The schedule carries one record per property, so loans secured by more than one property appear as several rows in a month; we collapse these to the loan-month level, which loses no loans. A loan is identified by the filer's central index key paired with its asset number. We collect the write-down date from Form 10-D filings through June 2026 and remove months on or after a loan's own write-down, so that every observation represents a month in which recognition was still open. After requiring the payment and status fields, our sample includes 298,979 loan-months on 6,104 loans in 118 deals carrying 93 distinct reporting-servicer labels, of which 199 loans record a write-down. Panel A of Table 1 reports the construction.

The coverage ratio and occupancy are available on roughly two thirds of the panel and are examined on that common subsample rather than imposed as controls in the main specification.

Table 1 presents descriptive statistics. SHORTFALL is present in 3.27% of loan-months and DELINQUENT 30+ in 1.23%, so the shortfall record is on roughly two and a half times as often as the classification it is being compared with.

Section 5.1 examines how SHORTFALL relates to the reported payment status and to eventual write-downs.

The rarity of the outcome matters for interpretation. About six loan-months in a thousand are followed by a write-down within twelve months. We therefore emphasize comparisons across measures, event coverage and unconditional rates rather than the level of a linear-model R-squared, which is difficult to interpret economically for a rare binary outcome.

4.3 Research design

To test H1 we estimate a linear probability model of an appraisal-reduction write-down on SHORTFALL and DELINQUENT 30+ entered jointly, a size control and fixed effects for the calendar quarter and for the month in which a loan enters the panel. Because the two enter jointly, the coefficient on SHORTFALL measures the incremental association of an outstanding advance conditional on the reported classification, and the coefficient on DELINQUENT 30+ measures the incremental association of the classification conditional on the advance. The outcome is partitioned into five future intervals that do not overlap, and the specification is

$$\mathrm{WD}(i, (t+lo, t+hi]) = \tag{1}$$

where WD(i, (t+lo, t+hi]) equals one if loan i records a write-down more than lo and no more than hi months after month t, over the intervals (0,12], (12,24], (24,36], (36,48] and (48,60]. SHORTFALL(i,t) and DELINQUENT 30+(i,t) are the two measures defined in Section 4.1, ln(BALANCE)(i,t) is the natural logarithm of the loan's outstanding balance, and $\delta_{q(t)}$ and $\varphi_{c(i)}$ are fixed effects for the calendar quarter of month t and for the month in which loan i enters the panel.

Windows that do not overlap are the specification throughout, because a cumulative window contains every write-down in the shorter windows it encloses and therefore cannot separate the horizons. H1 predicts that SHORTFALL retains a positive incremental association at horizons over which DELINQUENT 30+ does not, and that a payment shortfall the classification never recorded remains informative once the loan is reported clean again. The second prediction is tested on the restricted sample described in Section 5.3. Standard errors are two-way clustered by deal and by calendar month (Cameron et al. 2011). Deal and servicer fixed effects, property-type time effects and a conditional-at-risk specification enter additional analyses.

Two nonparametric comparisons supplement the regressions. The first dates the first month each measure is present before a write-down. The second reports the share of eventual write-downs each measure has reached by a given horizon. Discrimination and overall prediction error are reported in Table 4 (Hanley and McNeil 1982). Every regression requires complete forward follow-up. A loan-month enters the estimate for an interval only when its entire forward window closes inside the observed panel, and loan-months whose window would extend past December 2025 are dropped rather than coded zero. The sample therefore declines as the horizon lengthens, from 242,326 loan-months for the first interval to 61,183 for the last, and no observation is treated as a non-event merely because the panel ended first. Descriptive timing tests use write-down dates observed through June 2026; regression outcomes use only forward windows that close by December 2025.

5 Results

5.1 Construct validity of the payment-shortfall measure

Table 2 establishes what SHORTFALL measures. Panel A reports correlations. SHORTFALL and DELINQUENT 30+ correlate at 0.607, related but not identical, and both correlate only weakly with the coverage ratio and occupancy, at 0.162 and 0.112.

Panel B is the clearest evidence that the advance-based variable behaves like a measure of borrower payment trouble. The share of loan-months with advances outstanding rises monotonically with the reported payment status: 0.1% of current loan-months, 65.5% of grace-period months, 87.3% of months late by less than thirty days, 99.6% at thirty to fifty-nine days and 100% at sixty days and beyond. Performing-matured loans carry no missed installment and no advance. The measure moves with the reported severity of payment trouble without being the reported classification.

Panel C reports the joint occurrence. Of 298,979 loan-months, 3,685 carry both measures, 6,101 carry an outstanding advance with no classification, and five carry a classification with no outstanding advance. Nearly every classified loan-month also records an outstanding advance, whereas many loan-months with advances outstanding have not reached the thirty-day threshold.

Panel D reports coverage before recognition on the 199 loans that record a write-down. SHORTFALL precedes 191 of them and DELINQUENT 30+ precedes 171; twelve months ahead the counts are 102 and 50, and twenty-four months ahead 63 and 22. A McNemar test on the discordant pairs rejects equality at every horizon. This is descriptive rather than causal evidence, and first occurrence can come from an earlier shortfall episode that later cured. Appendix C therefore examines the final uninterrupted episode: within episodes that

eventually classify, the classification typically follows the continuing shortfall by a median of one month. The broader coverage difference arises partly because not every shortfall episode becomes classified, with 28 of the 191 final episodes never classified before the write-down, and partly because earlier payment history remains informative.

5.2 Payment shortfalls, delinquency classification and loss recognition

Table 3 reports the main result. Within twelve months both measures are strongly positive: SHORTFALL is 0.048 and DELINQUENT 30+ is 0.191, so once a loan is classified that status is much the stronger indicator of imminent recognition. Beyond twelve months the incremental associations separate. SHORTFALL remains positively associated with write-downs during the twelve-to-twenty-four and twenty-four-to-thirty-six month intervals, at 0.022 and 0.018, after controlling for DELINQUENT 30+, whereas DELINQUENT 30+ has no positive incremental association beyond the first twelve months, at 0.004 and then negative. At thirty-six to forty-eight months SHORTFALL is 0.009 and significant only at the 10% level, and at forty-eight to sixty months it is indistinguishable from zero. Evidence beyond thirty-six months is substantially weaker, and we do not rest any claim on it.

These estimates support H1. We do not read the negative DELINQUENT 30+ coefficients at the longer horizons as evidence that delinquency reduces the probability of a write-down. A loan classified today is usually resolved or written down before those windows open, so the later-horizon sample is increasingly selected toward loans that cured or otherwise avoided near-term recognition, and the coefficients reflect composition and resolution rather than an economic effect. The same caution applies to the mechanical link on the other side: an uncured sixty-day delinquency and transfer to special servicing are among the events that require a new appraisal (Carlson 2026), so the write-down process is mechanically related to

the classification, which should if anything strengthen its estimated association with the outcome.

5.3 Information in prior payment history

Table 4 asks whether the payment record is merely an earlier stage of the same deterioration. Panel A enters current state and prior history together, and shows that the two can coexist in one specification: with current SHORTFALL and DELINQUENT 30+ in the regression, a shortfall in the prior twenty-four months is 0.004 and 0.005 over the first two windows, significant at the 10% level, and a prior classification is insignificant throughout. This panel is supportive rather than decisive, since the prior-shortfall coefficients are significant only at the 10% level; Panel B is the sharper evidence on the prior-history prediction.

Panel B is the sharper test. We restrict the sample to loan-months in which SHORTFALL and DELINQUENT 30+ both equal zero and no classification appears anywhere in the preceding twenty-four months, so every observation is currently clean on both measures and has had no thirty-day classification during those two years. A shortfall in those twenty-four months still predicts recognition, at 0.003 over the following year and 0.006 over the second year. The unconditional rates beneath the estimates give the same comparison without a regression: the write-down rate over the first year is 0.516% following a prior shortfall against 0.183% otherwise, and over the second year 1.020% against 0.412%. This is the response to the objection that SHORTFALL is simply a delinquency episode that has not yet crossed thirty days. These loans have not crossed the thirty-day threshold in the preceding two years.

The result does not extend beyond two years. At twenty-four to thirty-six months the estimate is indistinguishable from zero, and at forty-eight to sixty months it is negative and significant, at -0.007, with an unconditional rate of 0.135% following a prior shortfall against 0.645% otherwise. We read this as survivorship rather than as an economic reversal. The later-horizon sample is increasingly selected toward loans that cured or otherwise avoided near-term recognition. We therefore confine the prior-history prediction to the two years over which the association is positive.

Panel B of Appendix D reports incremental discrimination and prediction error as in-sample diagnostics. Adding current SHORTFALL to the current classification raises the area under the receiver operating characteristic curve from 0.811 to 0.880 over the first year and from 0.624 to 0.675 over the second, and adding prior history raises it further, to 0.890 and 0.706. Payment history improves discrimination over the following two years. Improvements in overall prediction error are limited: the Brier score is essentially unchanged across the three predictor sets at every horizon, and at horizons beyond two years discrimination deteriorates when history is added. The evidence supports the narrower claim about the first two years and not a general improvement in forecasting.

5.4 Measurement and alternative credit-risk information

Table 5 tests the construction of SHORTFALL. The filed field is the outstanding balance of advances, so a positive value can persist after the month in which the advance was made. Panel A compares three advance constructions in otherwise identical specifications that omit the delinquency classification, so the coefficients are comparable within the panel rather than to Table 3: the baseline stock, the month in which the balance moves from zero to positive, and any increase in the balance. All three are positive and significant through twenty-four-to-

thirty-six months, at 0.015, 0.012 and 0.013 in that window, so the result is not produced by persistence in an outstanding balance. Panel B requires the shortfall to persist for two consecutive months, which rules out a result driven solely by a single noisy monthly observation; the coefficients are larger than the baseline through thirty-six months and marginal at thirty-six to forty-eight. Panel C restricts the sample to the grace-period and under-thirty-day payment-status codes and adds payment-status-code fixed effects, so the comparison is between loan-months carrying the same reported status. SHORTFALL is significant through twenty-four-to-thirty-six months there, at 0.029, 0.032 and 0.036. The result is therefore not an artifact of defining the measure from a stock, of one noisy monthly observation, or of sorting across reported delinquency categories.

Table 6 asks whether the result is other observable credit deterioration or an artifact of the thirty-day threshold. Panel A adds the coverage ratio and physical occupancy on the loan-months where both are populated. SHORTFALL remains significant through twenty-four-to-thirty-six months, at 0.051, 0.018 and 0.016. The coverage ratio is significant only at twelve to twenty-four months and marginally at forty-eight to sixty; occupancy is significant through thirty-six-to-forty-eight months but an order of magnitude below the shortfall coefficient in the first year. A coverage ratio based on borrower-reported income that is on average four quarters old will often not move contemporaneously when the borrower stops paying.

Panels B and C replace the thirty-day threshold with the sixty- and ninety-day thresholds. Under both, the classification retains a large positive association within twelve months and none beyond it, while SHORTFALL continues to be positively associated with write-downs at twelve to twenty-four and twenty-four to thirty-six months, at 0.026 and 0.018 against DELINQUENT 60+ and 0.026 and 0.017 against DELINQUENT 90+. The

incremental content of the payment record therefore does not depend on choosing a thirty-day threshold, and is not subsumed by contemporaneously observable property fundamentals.

5.5 Robustness and interpretation

Table 7 re-estimates the result under five variations. Panel A replaces the two indicators with mutually exclusive current combinations, excluding the five loan-months that carry a classification without an outstanding advance rather than estimating from them. Within twelve months the combined state is much more severe, at 0.239 against 0.047 for an outstanding advance alone, and the equality test rejects. At twelve to twenty-four and twenty-four to thirty-six months the two are statistically indistinguishable, with p of 0.677 and 0.379. We do not emphasize the equality tests at the two longest windows, because by then the classified group has become negatively selected and the comparison is not economically clean.

Panel B holds the sample fixed at the 61,183 loan-months with a complete sixty-month forward window, so the horizon pattern cannot be produced by the changing composition of the estimation sample. SHORTFALL is 0.060 within twelve months and 0.020 at twelve to twenty-four, both significant, and is 0.011 and insignificant at twenty-four to thirty-six. The twelve-to-twenty-four month result therefore survives the common-sample discipline; the twenty-four-to-thirty-six month result is supported in the baseline and several other specifications but not in this one. Panel C conditions each window on the loan remaining at risk when the window opens and supports SHORTFALL through thirty-six-to-forty-eight months, at 0.010. Panel D absorbs property-type-specific time shocks and supports it through twenty-four-to-thirty-six months, at 0.017, with the thirty-six-to-forty-eight estimate marginal.

Panel E reports deal and servicer fixed effects. Both preserve the longer-horizon association: SHORTFALL is 0.021 and 0.022 at twelve to twenty-four months and 0.016 and 0.020 at twenty-four to thirty-six, and the classification carries no positive incremental association beyond the first year under either. Advance behavior can differ across servicers, so the servicer specification matters for the interpretation of the measure, and the estimates are essentially unchanged.

Taken together, the pattern is robust to how the payment measure is constructed, to observable property fundamentals, to the choice of classification threshold, and to deal- and servicer-level heterogeneity. It is strongest over the first two years, supported in most specifications through three years, and weak thereafter.

6 Conclusion

This paper asks whether the borrower payment record contains information about subsequent loss recognition that the creditor's current delinquency classification does not capture. Commercial mortgage-backed securities disclose the borrower payment shortfall, the reported classification and the appraisal-reduction write-down separately on the same loan in the same monthly reporting cycle. Entered jointly, both measures predict recognition over the following year, and the classification is much the stronger indicator of imminent recognition. Beyond twelve months the classification has no positive incremental association, while the payment shortfall remains positively associated with write-downs over the twelve-to-twenty-four and twenty-four-to-thirty-six month windows. Among currently clean loans with no classification in the preceding twenty-four months, prior payment shortfalls predict recognition over the following year and more weakly over the second, after the loan is reported clean again. The classification and the payment history capture different dimensions

of the deterioration process: the classification is especially informative about immediacy, while the payment record contains information over longer horizons that the classification alone does not fully summarize.

The findings are subject to important limitations. The results establish information and timing rather than intent. The design does not distinguish deliberate deferral from ordinary processing, monitoring or workout frictions, it does not show that any creditor delayed classification, and it does not establish that waiting is inefficient. Within episodes that eventually classify, the classification follows the continuing shortfall by a median of about one month, and not every shortfall episode reaches the classification threshold. We do not propose SHORTFALL as a recognition rule: many payment problems cure, the measure is constructed from the outstanding balance of servicer advances rather than the amount advanced in the month, and it has a known limitation for maturity defaults that is contractual rather than incidental. Evidence beyond three years is weak in the baseline and is not established in the common-sample specification. And the setting is a securitization trust rather than a bank portfolio: the outcome is an appraisal-based write-down rather than an allowance, modification latitude is narrower, and the composition of loans that reach a trust differs systematically from those a bank retains (Black et al. 2017; Glancy et al. 2022a). Accordingly, neither the magnitudes nor the specific horizons estimated in CMBS should be assumed to generalize to bank portfolios.

We stop short of concluding that losses should be recognized when a payment shortfall appears, since a rule built on them would recognize losses for many shortfalls that subsequently cure, and the existence of a threshold is one reason a classification exists. The

results suggest that borrower-level payment information can complement, rather than replace, creditor-produced credit classifications.

Declarations

Competing interests None.

Data availability The loan-level data are publicly available on SEC EDGAR: the asset-level schedules filed on Form ABS-EE and the distribution reports filed on Form 10-D by CMBS trusts registered under Regulation AB II (SEC 2026). The code that builds the sample and the tables is available on request.

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Table 1

Sample construction and descriptive statistics

Panel A: Sample construction

Sample construction	Loan-months	Loans	Deals	Write-down loans
Asset-level records, November 2016 to December 2025	641,965			
Loan-level records after collapsing property rows	344,633	6,140	118	
Months before the loan's first write-down	338,606	6,140	118	
Payment and status fields available	298,979	6,104	118	
Final main estimation sample	298,979	6,104	118	199

Panel B: Descriptive statistics

Variable	N	Mean	SD	p25	Median	p75
SHORTFALL	298,979	0.033	0.178	0.000	0.000	0.000
DELINQUENT 30+	298,979	0.012	0.110	0.000	0.000	0.000
DELINQUENT 60+	298,979	0.008	0.090	0.000	0.000	0.000
DELINQUENT 90+	298,979	0.006	0.078	0.000	0.000	0.000
DSCR < 1	206,275	0.041	0.198	0.000	0.000	0.000
OCCUPANCY < 80%	207,043	0.163	0.369	0.000	0.000	0.000
LN(BALANCE)	298,420	16.218	1.024	15.483	16.195	16.973

Panel A reports the construction of the estimation sample from the asset-level schedules filed on Form ABS-EE between November 2016 and December 2025. Panel B describes the 298,979 loan-months in that sample. The unit of observation is the loan-month. The panel is serviced under 93 distinct reporting-servicer labels. Variable definitions are in Appendix A.

Table 2

Construct validity and the relation among credit-risk measures

Panel A: Pearson correlations

Variable	SHORTFALL	DQ 30+	DQ 60+	DQ 90+	DSCR < 1	OCC < 80%
SHORTFALL	1.000					
DELINQUENT 30+	0.607	1.000				
DELINQUENT 60+	0.494	0.813	1.000			
DELINQUENT 90+	0.426	0.700	0.862	1.000		
DSCR < 1	0.162	0.178	0.175	0.171	1.000	
OCCUPANCY < 80%	0.112	0.115	0.113	0.106	0.255	1.000

Panel B: SHORTFALL by reported payment-status code

Payment status	Loan-months	Loans	SHORTFALL present
0 Current	288,128	5,966	0.1%
A Grace period	1,602	734	65.5%
B Late, under thirty days	5,160	1,756	87.3%
1 Thirty to fifty-nine days	1,242	547	99.6%
2 Sixty to eighty-nine days	626	345	100.0%
3 Ninety days or more	1,822	305	100.0%
4 Performing matured	230	44	0.0%
5 Non-performing matured	169	30	100.0%

Panel C: Joint occurrence of SHORTFALL and DELINQUENT 30+

	DELINQUENT 30+ = 0	DELINQUENT 30+ = 1	Total
SHORTFALL = 0	289,188	5	289,193
SHORTFALL = 1	6,101	3,685	9,786
Total	295,289	3,690	298,979

Panel D: Coverage and advance warning before the write-down

Measure	WD loans preceded	Share of 199	≥ 12m ahead	≥ 24m ahead	≥ 36m ahead	≥ 48m ahead	≥ 60m ahead
SHORTFALL	191	96.0%	102	63	40	30	19
DELINQUENT 30+	171	85.9%	50	22	14	9	6

Panel A reports Pearson correlations. Panel B reports, for each payment status the servicer assigns, the share of loan-months with advances outstanding. Panel C cross-classifies every loan-month by the two measures. Panel D is measured on the 199 loans that record a write-down; a McNemar test on the discordant pairs rejects equality at every horizon. First occurrence can come from an earlier shortfall episode that later cured, and Appendix C examines the final uninterrupted episode.

Table 3

Payment shortfalls, delinquency classification and subsequent write-downs

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.048***	0.022***	0.018***	0.009*	-0.002
	(5.8)	(3.6)	(3.0)	(1.9)	(-0.7)
DELINQUENT 30+	0.191***	0.004	-0.007	-0.010***	-0.005**
	(8.1)	(0.4)	(-0.9)	(-2.6)	(-2.5)
Controls					
LN(BALANCE)	0.001***	0.002***	0.003***	0.003***	0.004***
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	162	147	120	88	57
Loan-months followed by a write-down	1,444	1,149	939	623	333
Observations	242,326	189,208	138,808	96,817	61,183
Within R-squared	0.120	0.004	0.002	0.002	0.003

The table reports linear probability models of an appraisal-reduction write-down on SHORTFALL and DELINQUENT 30+ entered jointly, so each coefficient measures the incremental association conditional on the other. The rule separates the estimated coefficients from the controls, fixed effects and sample composition. The five outcome windows do not overlap. A loan-month enters a column only when its complete forward window closes inside the observed panel. t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels. Standard errors are two-way clustered by deal and calendar month. Coefficients are reported to three decimal places.

Table 4

Information in prior payment shortfalls

Panel A: Current payment state and prior twenty-four-month payment history

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.059***	0.033***	0.026*	0.017	-0.006
	(5.2)	(2.8)	(1.7)	(1.0)	(-1.5)
DELINQUENT 30+	0.157***	-0.014	-0.019	-0.017	-0.003
	(4.9)	(-0.7)	(-1.0)	(-1.0)	(-0.5)
PAST SHORTFALL, prior 24m	0.004*	0.005*	-0.001	0.003	-0.006**
	(1.8)	(1.7)	(-0.3)	(0.6)	(-2.5)
PAST DELINQUENT 30+, prior 24m	0.003	0.008	0.003	-0.007	0.006
	(0.6)	(1.2)	(0.7)	(-0.8)	(0.6)
Controls					
LN(BALANCE)	0.002**	0.003***	0.005***	0.007***	0.007**
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	84	65	43	25	15
Loan-months followed by a write-down	721	484	258	137	55
Observations	114,293	76,260	44,882	22,064	9,343
Within R-squared	0.110	0.008	0.006	0.008	0.007

Panel B: Currently clean loans with no DELINQUENT 30+ in the prior twenty-four months

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
PAST SHORTFALL, prior 24m	0.003**	0.006*	0.000	0.004	-0.007***
	(2.2)	(1.9)	(-0.1)	(0.8)	(-2.8)
Controls					
LN(BALANCE)	0.002***	0.003***	0.005***	0.007***	0.008**
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	59	53	37	24	14
Loan-months followed by a write-down	243	350	209	126	52
Observations	107,431	71,003	41,061	20,067	8,643
Within R-squared	0.002	0.003	0.004	0.007	0.009
Raw write-down rates					
No prior SHORTFALL	0.183%	0.412%	0.486%	0.572%	0.645%
Prior SHORTFALL	0.516%	1.020%	0.663%	1.115%	0.135%
Ratio, prior to no prior SHORTFALL	2.82×	2.48×	1.36×	1.95×	0.21×

PAST SHORTFALL and PAST DELINQUENT 30+ equal one when the measure was present in any of the twenty-four months preceding the current observation, excluding the current month. Panel A enters current state and prior history together. Panel B restricts the sample to loan-months in which both current measures equal zero and no classification appears anywhere in the prior twenty-four months, so there is no current classification coefficient; unconditional write-down rates in that sample appear beneath the estimates. The five outcome windows do not overlap. A loan-month enters a column only when its complete forward window closes inside the observed panel. t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels. Standard errors are two-way clustered by deal and calendar month. Coefficients are reported to three decimal places.

Table 5

Alternative constructions of SHORTFALL

Panel A: Alternative advance constructions

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
Positive outstanding advance	0.118***	0.024***	0.015***	0.005	-0.004*
	(8.9)	(3.6)	(2.9)	(1.3)	(-1.6)
Zero-to-positive advance onset	0.033***	0.015***	0.012***	0.002	0.001
	(4.5)	(3.3)	(3.1)	(0.6)	(0.2)
Increase in the advance balance	0.125***	0.020***	0.013***	0.004	-0.003
	(8.4)	(3.4)	(3.0)	(1.2)	(-1.4)
Controls					
LN(BALANCE)	Yes	Yes	Yes	Yes	Yes
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month

Panel B: SHORTFALL required to persist for two consecutive months

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL, two consecutive months	0.064***	0.032**	0.026**	0.017*	-0.004
	(5.1)	(2.5)	(2.2)	(1.8)	(-1.2)
DELINQUENT 30+	0.177***	-0.004	-0.015	-0.017**	-0.003**
	(7.5)	(-0.3)	(-1.2)	(-2.3)	(-2.4)
Controls					
LN(BALANCE)	0.001***	0.002***	0.003***	0.003***	0.004***
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	162	147	120	88	57
Loan-months followed by a write-down	1,444	1,149	939	623	333
Observations	242,326	189,208	138,808	96,817	61,183
Within R-squared	0.118	0.003	0.002	0.002	0.003

Panel C: Within the grace-period and under-thirty-day payment-status codes

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.029**	0.032**	0.036**	0.009	-0.003
	(2.4)	(2.3)	(2.5)	(1.1)	(-1.1)
Controls					
LN(BALANCE)	0.001	0.004	0.002	-0.003	0.001
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Payment-status-code fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Observations	5,610	4,573	3,812	2,993	1,952

Each row of Panel A is a separate regression, estimated with the same controls and fixed effects as Table 3 and without the delinquency classification, so the three constructions are comparable with one another rather than with the joint estimates in Table 3. The baseline is a positive outstanding principal-and-interest advance balance; the onset measure is a move from zero to positive; the increase measure is any rise in the balance. Panel B requires the shortfall to persist for two consecutive months. Panel C restricts the sample to payment-status codes A and B, on which DELINQUENT 30+ equals zero by construction, so there is no classification row. t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels. Standard errors are two-way clustered by deal and calendar month. Coefficients are reported to three decimal places.

Table 6

Alternative credit-risk information and delinquency thresholds

Panel A: Property fundamentals

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.051***	0.018***	0.016**	0.011	-0.005
	(4.7)	(3.1)	(2.0)	(1.5)	(-1.2)
DELINQUENT 30+	0.193***	-0.004	-0.012	-0.013**	-0.008***
	(6.0)	(-0.6)	(-1.1)	(-2.1)	(-2.8)
Controls					
DSCR < 1	0.007	0.015**	0.003	-0.001	0.016*
OCCUPANCY < 80%	0.006**	0.011***	0.012***	0.007**	-0.001
LN(BALANCE)	0.002***	0.003***	0.003***	0.004***	0.005***
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	132	106	89	63	39
Loan-months followed by a write-down	992	750	560	350	196
Observations	166,168	129,919	94,645	62,818	35,930
Within R-squared	0.119	0.009	0.006	0.004	0.005

Panel B: DELINQUENT 60+ benchmark

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.068***	0.026***	0.018***	0.008*	-0.002
	(6.8)	(3.7)	(3.1)	(1.9)	(-0.9)
DELINQUENT 60+	0.201***	-0.010	-0.011	-0.011***	-0.007***
	(5.7)	(-0.9)	(-1.1)	(-3.3)	(-3.0)
Controls					
LN(BALANCE)	0.001**	0.002***	0.003***	0.003***	0.004***
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	162	147	120	88	57
Loan-months followed by a write-down	1,444	1,149	939	623	333
Observations	242,326	189,208	138,808	96,817	61,183
Within R-squared	0.115	0.004	0.002	0.002	0.003

Panel C: DELINQUENT 90+ benchmark

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.088***	0.026***	0.017***	0.007*	-0.002
	(7.6)	(3.8)	(3.1)	(1.8)	(-1.0)
DELINQUENT 90+	0.159***	-0.010	-0.012	-0.013***	-0.009***
	(3.9)	(-0.9)	(-1.1)	(-3.6)	(-3.2)
Controls					
LN(BALANCE)	0.001**	0.002***	0.003***	0.003***	0.004***
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	162	147	120	88	57
Loan-months followed by a write-down	1,444	1,149	939	623	333
Observations	242,326	189,208	138,808	96,817	61,183
Within R-squared	0.094	0.004	0.002	0.002	0.003

Panel A adds the coverage ratio and physical occupancy on the loan-months where both are populated. Panels B and C replace the thirty-day threshold with the sixty- and ninety-day thresholds. The five outcome windows do not overlap. A loan-month enters a column only when its complete forward window closes inside the observed panel. t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels. Standard errors are two-way clustered by deal and calendar month. Coefficients are reported to three decimal places.

Table 7

Robustness and interpretation of the main result

Panel A: Mutually exclusive overlap decomposition

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL only	0.047***	0.022***	0.018***	0.009*	-0.002
	(5.8)	(3.6)	(3.0)	(1.9)	(-0.7)
SHORTFALL and DELINQUENT 30+	0.239***	0.026**	0.010	-0.001	-0.007***
	(9.4)	(2.6)	(1.5)	(-0.3)	(-2.7)
Wald test: coefficients equal (p-value)	<0.001	0.677	0.379	0.009	0.014
Controls					
LN(BALANCE)	0.001***	0.002***	0.003***	0.003***	0.004***
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	162	147	120	88	57
Loan-months followed by a write-down	1,444	1,149	939	623	333
Observations	242,322	189,206	138,806	96,816	61,182
Within R-squared	0.120	0.004	0.002	0.002	0.003

Panel B: Common sixty-month follow-up sample

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.060***	0.020**	0.011	0.006	-0.002
	(3.7)	(2.0)	(1.6)	(1.4)	(-0.7)
DELINQUENT 30+	0.235***	0.002	-0.009**	-0.005	-0.005**
	(8.0)	(0.2)	(-2.0)	(-1.5)	(-2.5)
Controls					
LN(BALANCE)	0.001	0.002	0.001	0.002***	0.004***
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	75	76	64	51	57
Loan-months followed by a write-down	675	616	510	351	333
Observations	61,183	61,183	61,183	61,183	61,183
Within R-squared	0.145	0.002	0.001	0.001	0.003

Panel C: Conditional-at-risk specification

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.048***	0.023***	0.019***	0.010**	-0.001
	(5.8)	(3.6)	(3.0)	(2.0)	(-0.4)
DELINQUENT 30+	0.191***	0.012	-0.004	-0.009**	-0.005*
	(8.1)	(1.0)	(-0.4)	(-2.1)	(-1.8)
Controls					
LN(BALANCE)	0.001***	0.002***	0.003***	0.003***	0.004***
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	162	147	120	88	57
Loan-months followed by a write-down	1,444	1,149	939	623	333
Observations	242,326	188,169	137,083	94,670	59,031
Within R-squared	0.120	0.004	0.002	0.002	0.003

Panel D: Property type by year-quarter fixed effects

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL	0.045***	0.021***	0.017***	0.007*	0.000
	(5.8)	(3.4)	(3.0)	(1.7)	(-0.1)
DELINQUENT 30+	0.190***	0.007	-0.005	-0.006*	-0.004*
	(8.4)	(0.7)	(-0.6)	(-1.8)	(-1.7)
Controls					
LN(BALANCE)	0.001	0.001**	0.002**	0.002***	0.003***
Fixed effects and inference					
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Property type × year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month
Sample and fit					
Distinct future write-down loans	162	147	120	88	57
Loan-months followed by a write-down	1,444	1,149	939	623	333
Observations	242,326	189,208	138,808	96,817	61,183
Within R-squared	0.113	0.003	0.002	0.001	0.001

Panel E: Deal and servicer fixed effects

Variable	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
SHORTFALL, deal fixed effects	0.050***	0.021***	0.016***	0.008*	-0.001
	(5.8)	(3.3)	(2.7)	(1.7)	(-0.6)
DELINQUENT 30+, deal fixed effects	0.192***	0.003	-0.007	-0.010***	-0.005**
	(8.2)	(0.3)	(-0.9)	(-2.7)	(-2.4)
SHORTFALL, servicer fixed effects	0.048***	0.022***	0.020***	0.009*	-0.004
	(5.3)	(3.2)	(3.0)	(1.7)	(-1.6)
DELINQUENT 30+, servicer fixed effects	0.193***	0.005	-0.007	-0.009**	-0.004*
	(7.9)	(0.5)	(-0.8)	(-2.3)	(-1.7)
Controls					
LN(BALANCE)	Yes	Yes	Yes	Yes	Yes
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Deal or servicer fixed effects	As indicated	As indicated	As indicated	As indicated	As indicated
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month

Panel A replaces the two indicators with mutually exclusive current combinations; the five loan-months carrying a classification without an outstanding advance are excluded rather than estimated, and the reported test is of equality of the two category coefficients within that regression. Panel B holds the sample fixed at the 61,183 loan-months with a complete sixty-month forward window. Panel C conditions each window on the loan remaining at risk when the window opens. Panel D absorbs property-type-specific time shocks. Panel E reports deal and servicer fixed effects, each in a separate regression. t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels. Standard errors are two-way clustered by deal and calendar month. Coefficients are reported to three decimal places.

Appendix A Variable definitions

Variable	Definition	Source
WD (lo, hi]	Equals one when the loan records an appraisal-reduction write-down more than lo and no more than hi months after the observation month.	Form 10-D
SHORTFALL	Equals one when the outstanding balance of principal-and-interest advances is positive, indicating an outstanding servicer advance generated by borrower nonpayment. The field is a stock as of the reporting date rather than the amount advanced in the month.	Form ABS-EE
SHORTFALL, two months	Equals one when SHORTFALL equals one in the current and the immediately preceding monthly observation.	Form ABS-EE
PAST SHORTFALL, prior 24m	Equals one when SHORTFALL was present in any of the twenty-four calendar months preceding the current observation. The current month is excluded.	Form ABS-EE
Payment-status code	Servicer payment status: 0 current; A grace period; B late but under thirty days; 1 thirty to fifty-nine days; 2 sixty to eighty-nine days; 3 ninety days or more; 4 performing matured; 5 non-performing matured.	Form ABS-EE
DELINQUENT 30+	Equals one for payment-status codes 1, 2 or 3.	Form ABS-EE
ADVANCE ONSET	Equals one when the outstanding advance balance moves from zero to positive between the previous monthly observation and the current one.	Form ABS-EE
ADVANCE INCREASE	Equals one when the outstanding advance balance is higher than in the previous monthly observation.	Form ABS-EE
DELINQUENT 60+	Equals one for payment-status codes 2 or 3.	Form ABS-EE
DELINQUENT 90+	Equals one for payment-status code 3.	Form ABS-EE
PAST DELINQUENT 30+, prior 24m	Equals one when DELINQUENT 30+ was present in any of the twenty-four calendar months preceding the current observation. The current month is excluded.	Form ABS-EE
DSCR < 1	Equals one when the most recently reported debt-service coverage ratio based on net operating income is below one.	Form ABS-EE
OCCUPANCY < 80%	Equals one when the most recently reported physical occupancy is below 80%.	Form ABS-EE
LN(BALANCE)	Natural logarithm of the outstanding loan balance in the observation month.	Form ABS-EE
Year-quarter fixed effects	Fixed effects for the calendar quarter containing the observation month.	Constructed
Entry-cohort fixed effects	Fixed effects for the month in which the loan first enters the panel.	Constructed
Deal and servicer fixed effects	Fixed effects for the securitization trust and for the reporting servicer.	Constructed
Deal and month clustering	Two-way clustered standard errors by securitization deal and calendar month.	Inference design

Appendix B The story of a loan

The evidence in the paper is an average taken over thousands of loans. This appendix follows one of them, to show what the three records look like month by month on a single asset and where the interval between them comes from. The loan is one of the 199 in the analysis panel with a write-down observed through June 2026. It is secured by a multifamily property, carries a balance of $15.4 million, and enters the panel in August 2022.

For its first twenty-three months the three records agree. The borrower pays on schedule, the master servicer advances nothing, the payment-status field reads current, and the trust reports no reduction. The property measures over this period read a debt service coverage ratio of 1.24 and physical occupancy of 94%.

In July 2024 the scheduled installment does not arrive and the master servicer funds it, recording an advance of $78,861. The payment status moves to the late-but-under-thirty-days code, on which the thirty-day indicator equals zero by construction. The coverage ratio still reads 1.24 and occupancy still reads 94%, because both are drawn from statements the borrower filed before the payments stopped.

The classification follows three months later. In October 2024 the field moves to the thirty-day threshold, by which point the advance has run for four consecutive months. The property measures move a month after that: in November 2024 the coverage ratio falls below one, to 0.998, and occupancy falls to 85%. On this loan, the advance begins in July 2024, DELINQUENT 30+ begins in October 2024, and the reported property measures deteriorate in November 2024.

The trust records an appraisal reduction of $1.85 million in May 2026, which falls after the last month of the predictor panel and is observed because write-down dates are collected

through June 2026, twenty-two months after the first advance and nineteen months after the first thirty-day classification.

Exhibit B1

The three records on one loan

Month	Advance outstanding	Payment status	DSCR	Occupancy	Write-down
Jun 2024	none	0, current	1.243	94%	none
Jul 2024	78,861	B, late under thirty days	1.243	94%	none
Aug 2024	81,490	B, late under thirty days	1.243	94%	none
Sep 2024	81,490	B, late under thirty days	1.243	94%	none
Oct 2024	78,861	1, thirty to fifty-nine days	1.243	94%	none
Nov 2024	160,350	1, thirty to fifty-nine days	0.998	85%	none
Dec 2024 to Mar 2025	78,861 to 162,979	1, thirty to fifty-nine days	0.998	85%	none
Apr 2025	none	0, current	0.998	85%	none
May 2025	none	0, current	0.998	85%	none
Jun 2025	81,490	B, late under thirty days	0.998	85%	none
Jul 2025 to Dec 2025	78,861 to 162,979	B, then 1 from Aug 2025	0.998	85%	none
May 2026	—	—	—	—	$1,853,777

Advance outstanding is the outstanding principal-and-interest advance balance reported on the asset-level schedule. Payment status is the reported code: 0 is current, B is a late payment less than thirty days delinquent, and 1 is thirty to fifty-nine days past due. DSCR and occupancy are the most recently reported figures for the collateral. The appraisal reduction is dated from Form 10-D and falls after the last month of the predictor panel, so it does not enter the regression outcomes. Dollar amounts are as filed.

The example also illustrates interruptions in the advance series. In April and May 2025 the advance stops and the status returns to current for two months before both resume, which is the kind of interruption the persistence variant in Section 5.4 is built to absorb. Nothing in this sequence establishes that the trust could have recognized the loss earlier than it did. What it establishes is that two records of the same deterioration became available at different dates, and that the payment-shortfall indicator became available first.

Appendix C The final shortfall spell before the write-down

Diagnostic	N	Share of write-down loans	Median months	Mean months
Final SHORTFALL run to the write-down	191	96.0%	7	8.7
DELINQUENT 30+ in the final run to the write-down	163	81.9%	6	7.7
Final SHORTFALL run to DELINQUENT 30+	163	81.9%	1	1.4
Final runs never classified before the write-down	28	14.1%	—	—

The table measures the same intervals as the descriptive timing analysis in Table 2, from the final uninterrupted run of advances that ends in recognition, rather than from the first month the measure is ever present. Measured this way the run precedes the write-down by a median of seven months and the classification raised during it by six, and the classification follows the start of the run by a median of one month, which is the reporting convention rather than a judgment. On twenty-eight of the 191 loans the final run is never classified before the write-down.

Appendix D Additional specifications

Panel A repeats the specification of Table 3 under two further variations. The first removes the balance control. The second restricts the sample to loans that record an outstanding advance at some point in their history, so that the comparison is not between loans that ever miss a payment and loans that never do. Panel B reports the area under the receiver operating characteristic curve and the Brier score for three nested predictor sets, computed in sample; Brier scores are multiplied by 100. t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels.

Panel A: Alternative controls and sample

Specification	WD (0,12]	WD (12,24]	WD (24,36]	WD (36,48]	WD (48,60]
No balance control, SHORTFALL	0.048***	0.022***	0.018***	0.009**	-0.001
	(5.8)	(3.6)	(3.0)	(2.0)	(-0.5)
No balance control, DELINQUENT 30+	0.191***	0.004	-0.007	-0.010***	-0.005**
	(8.1)	(0.4)	(-0.9)	(-2.7)	(-2.5)
Loans that ever record a shortfall, SHORTFALL	0.043***	0.015**	0.012**	0.002	-0.011***
	(5.7)	(2.5)	(2.1)	(0.3)	(-3.1)
Loans that ever record a shortfall, DELINQUENT 30+	0.189***	0.005	-0.006	-0.010**	-0.008**
	(8.2)	(0.6)	(-0.7)	(-2.4)	(-2.5)
Fixed effects and inference					
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Entry-cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Deal + month	Deal + month	Deal + month	Deal + month	Deal + month

Panel B: Incremental discrimination and prediction error

Outcome window	AUC: current DQ	AUC: adding current SF	AUC: adding history	Brier × 100: current DQ	Brier × 100: adding current SF	Brier × 100: adding history
WD (0,12]	0.811	0.880	0.890	0.578	0.571	0.571
WD (12,24]	0.624	0.675	0.706	0.631	0.629	0.631
WD (24,36]	0.717	0.733	0.713	0.570	0.570	0.572
WD (36,48]	0.710	0.691	0.654	0.616	0.619	0.620
WD (48,60]	0.750	0.755	0.738	0.580	0.580	0.581