Losing Control?
The Two-Decade Decline in Loan Covenant Violations*

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September 2023

Abstract

The annual proportion of U.S. public firms that reported a financial covenant violation fell roughly 70% between 1997 and 2019. To understand this trend, we develop an estimable model of covenant design that depends on the ability to discriminate between distressed and non-distressed borrowers and the relative costs associated with screening incorrectly. We find the drop in violations is best explained by an increased willingness to forego early detection of distressed borrowers in exchange for fewer inconsequential violations, which we attribute mostly to a shift in the composition of public firms and partly to heightened investor sentiment during the 2010s.

Keywords: financial contracting, control rights, financial covenants, credit agreements
JEL Classification: G21, G23, G32, G34

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* We thank participants at the annual meetings for the American Finance Association (2021), European Finance Association (2020), Financial Management Association (2020), Northern Finance Association (2020), SFS Cavalcade North America (2020); conference participants at the Drexel University Corporate Governance Conference, Philly Five Conference, RCFS/RAPS Conference at Baha Mar, and Washington University Conference on Corporate Finance; seminar participants at Booth School of Business (University of Chicago), Darden School of Business (University of Virginia), Federal Reserve Bank of Philadelphia, Federal Reserve Board of Governors, Norwegian School of Economics (NHH), OsloMet Business School, Queen's University, UC Berkeley School of Law, Syracuse University, University of Cincinnati, and Villanova University; and comments from Ken Ayotte, Adam Badawi, Øyvind Bøhren, Sudheer Chava, Gabriel Chodorow-Reich, Larry Halperin, Chris James, Stephen Karolyi, Yueran Ma, Raghu Rajan, Michael Roberts, Michael Schwert, and Dragon Tang.

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1 Introduction

Theorists and practitioners view debt covenants as important tools for managing the credit risk of corporate borrowers (see, e.g., Tirole, 2010; Simpson, Thacher, and Bartlett, 2022). Financial covenants, in particular, serve as "tripwires" that aid in monitoring borrower performance and grant creditors the right to sever lending commitments, recall outstanding debt, and foreclose on collateral if the borrower breaches a contractual threshold. A large body of empirical research documents the widespread use of financial covenants and shows that lenders use their bargaining power after a covenant violation to renegotiate terms and influence borrower investment and financing decisions.[1]

This paper documents that the incidence of financial covenant violations among U.S. public firms has fallen dramatically over the last two decades. Using newly collected data from SEC filings, we show that the annual proportion of U.S. public firms that reported a violation decreased by roughly 70% from 1997 to 2019. The decline in violations coincides with a substantial reduction in covenant restrictiveness. We find that the average loan package to U.S. public firms in 2019 contained almost half as many financial covenants as the average loan in 1997 and the covenants that remained were set at looser thresholds. To investigate the causes and consequences of this trend, we develop a simple model of optimal covenant design that balances the benefits and costs of restrictive financial covenants and use the model to empirically decompose the trend into its fundamental drivers.

Understanding the economic mechanisms behind the aggregate decline in financial covenant violations is important due to the implications for financial stability. First, loose financial covenants limit the ability of lenders to monitor borrowers, potentially exacerbating the costs

[1] See, e.g. Chava and Roberts (2008), Roberts and Sufi (2009a), Nini, Smith, and Sufi (2009, 2012), Falato and Liang (2016), Freudenberg, Imbierowicz, Saunders, and Steffen (2017), Chava, Nanda, and Xiao (2017), Ferreira, Ferreira, and Mariano (2018), Balsam, Gu, and Mao (2018), Ersahin, Irani, and Le (2021), Becher, Griffin, and Nini (2021).

associated with financial distress. As noted by Sufi and Taylor (2022), "the ultimate trigger of the financial crises that lead to lower growth is an adverse shock in the financial sector." Second, loose financial covenants could be a symptom of excessively generous credit supply, driven perhaps by low interest rates, prolonged accommodative monetary policy, or changes in the types of creditors providing loans. Kashyap and Stein (2023) establish that various indicators of elevated "financial-market sentiment" – which include alternative measures of bank lending standards – are correlated with a higher likelihood of a financial crisis and worse macroeconomic outcomes.

In our model, restrictive financial covenants are beneficial because they provide lenders with the opportunity to catch borrower performance declines early and take steps to protect their financial claim (Townsend, 1979; Gale and Hellwig, 1985; Williamson, 1987). Adopting terminology from medical diagnostic testing, restrictive covenants have a lower probability of a *false negative* outcome in which the borrower is distressed but fails to violate. We quantify the average cost of a false negative using default data from Moody's and find that recovery rates are 7 to 11 percentage points lower for firms that did not violate a covenant prior to bankruptcy. If the trend in violations reflects a substantial increase in false negatives, the shift toward looser covenants could generate larger default-related losses in the financial sector.

Restrictive covenants are also costly, however, because they require lender monitoring, reduce borrower operational flexibility, and induce frequent renegotiations (Smith and Warner, 1979; Berlin and Mester, 1992). Because financial covenants are written on performance metrics that imperfectly measure financial distress, restrictive covenants have a higher probability of a *false positive* outcome in which the borrower violates despite not being financially distressed. We document that over half of our sample violations are resolved with no consequential change to the lending arrangement. If the observed decline in violations consists of a substantial decrease in false positives, the trend toward looser covenants creates much less concern about potential losses in the financial sector.

Based on the logic of the model, we decompose the covenant violation rate into three factors: (1) the true positive rate (TPR), defined as the fraction of distressed borrowers that violate a covenant, (2) the false positive rate (FPR), defined as the fraction of non-distressed borrowers that violate a covenant, and (3) the corporate distress rate. Conceptually, we consider a firm to be distressed if lenders would choose to renegotiate terms of the lending arrangement if they had the right to do so. Empirically, we code covenant violators as distressed if the violation led to a consequential renegotiation of the lending arrangement, which we determine by reading loan amendments filed with the SEC. Consequential renegotiations (*true positives*) include interest rate increases, loan commitment reductions, principal repayment requirements, and forced capital raises or asset sales. Conversely, we consider "waiver only" outcomes as recognition that the violation was a false positive because, upon further monitoring, the lender made no major change to the lending arrangement. For non-violating firms, we rely on future bankruptcy filings as our proxy of financial distress, under the assumption that lenders would have renegotiated the loan terms if the borrower had violated a covenant prior to bankruptcy. We code a firm that fails to violate a covenant but files for bankruptcy within one year as a false negative and all other non-violators as *true negatives*.[2]

The empirical decomposition produces several facts. First, the largest component of the downward trend in violations consists of a drop in the number of false positive violations. The FPR falls from over 5% during the late 1990s to under 0.5% by 2019, a 90% decrease that explains 61% of the overall decline in violations. Second, the corporate distress rate varies cyclically but declines during the latter part of the sample, explaining another 25% of the total drop in violations. Finally, the frequency at which truly distressed borrowers violate a covenant

[2] As described more fully below, we examine the robustness of our results using alternative approaches to measure distress for non-violating firms.

– the TPR – remains relatively constant above 70% over the first two-thirds of the sample period but falls to near 50% following the financial crisis, explaining the remaining 14% of the total decline in violations. These facts imply that the aggregate decline in financial covenant violations does not primarily reflect a deterioration in the ability of lenders to monitor distressed borrowers.

To further assess the mechanisms behind the trend, we return to our model of optimal covenant design. Under the assumption that loan parties select covenant thresholds to minimize the expected total cost of false positives and false negatives, the model identifies two fundamental factors that influence the optimal threshold. First, the threshold depends on the ability of covenants to discriminate between distressed and non-distressed borrowers, which we refer to as the covenant "technology." Better technology allows covenants to catch more truly distressed borrowers without increasing the number of false positives. Second, the threshold depends on the ratio of the expected costs of false positives to false negatives, which we refer to as loan party "preferences." The optimal covenant is less restrictive when this ratio is larger, reflecting a willingness to forego early detection of some distressed borrowers in exchange for fewer inconsequential violations.

We extract the parameters of the covenant design model from the estimated realizations of the TPR and FPR. Our estimates imply a sharp rise in the relative cost of false positives, with the preference parameter estimate nearly doubling from 1997-2003 to 2004-2011 and then quintupling in 2012-2019. Meanwhile, we find a slight improvement in covenant technology, particularly during the 2004-2011 period, which mitigates the decline in the TPR while accelerating the decline in the FPR. These findings imply that the overall covenant violation trend is best attributed to an increased preference to trade off a modestly lower TPR for a substantially lower FPR, paired with a small improvement in covenant technology.

We next assess the extent to which observable changes in the corporate loan market explain the drop in violations. Borrowers at the end of the sample period are larger and healthier than twenty years prior (Kahle and Stulz, 2017), lenders are more transactional and dispersed (Becker and Ivashina, 2016), and financial covenants are less likely to be written on balance sheet metrics (Demerjian, 2011). These features correlate with violation status in intuitive ways; for example, the FPR and TPR are decreasing in firm size, consistent with large borrowers having higher renegotiation costs. Using a Blinder-Oaxaca decomposition, we separate changes in the TPR and FPR that can be explained by compositional changes from what is left unexplained. The analysis shows that a small set of characteristics – borrower size, borrower credit rating, lender type, loan market segment, and reliance on balance sheet covenants – can explain 52% of the total fall in the FPR and 69% of the drop in the TPR. Together with the falling distress rate, observable changes in the loan market explain 68% of the overall decline in violations. We show that improvements in the covenant technology parameter are associated with the observable switch from the reliance on balance-sheet covenants to cash-flow covenants in loan agreements. Similarly, larger borrowers and transactional lenders are associated with less restrictive covenants, so estimated preferences loosened as these became a larger share of the market.

We conclude our analysis by using the unexplained changes in the TPR and FPR to estimate how model parameters would have evolved absent the shift in borrower, lender, and loan characteristics through time. The counterfactual estimates show that the technology parameter would have risen during 2004-2011 and then declined to its original level in 2012-2019, while the preference parameter would have almost doubled over the entire period. The unexplained drops in the FPR and the TPR after 2012 indicate an increased willingness to accept false negatives during a period of low interest rates and generous credit supply, suggesting the shift toward looser covenants was partly driven by heightened investor sentiment.

Our paper contributes to the literature studying the design and renegotiation of debt contracts. It builds on prior research that justifies the existence of financial covenants (e.g., Aghion and Bolton, 1992; Berlin and Mester, 1992; Garleanu and Zwiebel, 2009) by modeling the optimal threshold as a function of their ability to screen for financial distress and the relative costs associated with screening incorrectly. Applying the model to understand the steep drop in public firm covenant violations observed over the previous two decades, we find that most of the fall can be explained by a large reduction in false positives and a decline in the public company distress rate, which in turn, is largely attributable to a shift in the composition of public firms towards larger borrowers that raise debt from transactional lenders. Although we do observe an unexplained drop in the TPR since 2012 that coincides with indicators of heightened financial market sentiment, our estimates imply that the potential aggregate cost associated with this decline is relatively mild. Together, our results help alleviate concerns voiced by policymakers about the financial stability risks posed by excessively loose covenants by showing that the two-decade decline in financial covenant violations among U.S. public firms does not primarily reflect a deterioration in the ability of lenders to monitor distressed borrowers.[3]

2 Background and Aggregate Trends

2.1 Financial Covenants in Debt Agreements

Covenants are widely recognized as important components of lending arrangements. Jensen and Meckling (1976) argue that covenants exist, in part, to constrain opportunistic behavior by corporate managers, while Smith and Warner (1979) emphasize that covenants are designed to

[3] The Federal Reserve Board's 2013 "Interagency Guidance on Leveraged Lending" notes, "weak initial underwriting of transactions, coupled with poor structure and limited covenants, may make problem credit discussions and eventual restructurings more difficult for an institution as well as result in less favorable outcomes" (https://www.federalreserve.gov/supervisionreg/srletters/sr1303a1.pdf). More recently, Senator Elizabeth Warren warned that, "the large leveraged lending market exhibits many of the characteristics of the pre-2008 subprime mortgage market. These loans are generally poorly underwritten and include few protections for lenders." (https://www.warren.senate.gov/download/letter-to-regulators-on-leveraged-lending)

minimize conflicts of interest between lenders and shareholders.[4] More recently, a legal guide summarizes the role of covenants as striking a balance to "protect the investors' ability to be paid . . . while preserving the issuer's ability to run its business and grow without undue restrictions" (Simpson, Thacher & Bartlett, 2022).

Financial covenants serve as "tripwires" that transfer control rights to lenders when verifiable financial ratios drop below contractual thresholds (Smith, 1993; Dichev and Skinner, 2002).[5] Due to the high monitoring and renegotiation costs of public debt, financial covenants are predominately found in private debt agreements. The breach of a financial covenant constitutes an event of default and grants lenders the right to sever all lending commitments, recall outstanding debt, and proceed to foreclose on collateral. In practice, lenders typically do not initiate default rights upon a violation, preferring instead to conduct a more thorough check of the borrower's credit quality and renegotiate terms of the loan contract if needed. The renegotiation addresses two issues. First, the borrower must cure the existing violation to return to compliance with the loan contract. This is typically achieved through a legal waiver in which lenders agree to excuse the borrower from covenant compliance for a fixed period. Second, the lender may require that the borrower agree to amend certain terms of the loan agreement in exchange for a waiver.

A large empirical literature shows that violations can lead to substantive amendments to the loan agreement (Roberts and Sufi, 2009b; Nini, Smith, and Sufi, 2012) as well as changes in borrower investment and financial policies, including reductions in debt issuance (Roberts and

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[4] The typical credit agreement contains affirmative, negative, and financial covenants. Affirmative and negative covenants minimize incentive conflicts by contracting directly on certain events, such as the distribution of dividends or issuance of additional debt. Nini and Smith (2023) provide a detailed review of covenants in debt agreements and related academic studies. Ivashina and Vallee (2022) offer a recent study of negative covenants in credit agreements.

[5] Financial covenants, as we use the term throughout the paper, are "maintenance" covenants that require compliance checks on a regular (usually, quarterly) basis. Public bond and leveraged loan contracts can also contain financial ratio thresholds in "incurrence" covenants, but these thresholds are checked only upon the incurrence of certain events, such as an acquisition or change of control. Bräuning, Ivashina, and Ozdagli (2022) offer a recent study of incurrence covenants in credit agreements.

Sufi, 2009a), capital expenditures (Chava and Roberts, 2008; Nini, Smith, and Sufi, 2009, Ersahin, Irani, and Le, 2021), R&D expenses and patent quantities (Chava, Nanda, and Xiao, 2017; Gu, Mao, Tian 2017), employment (Falato and Liang, 2016; Ersahin, Irani, and Le, 2021), and shareholder payouts (Nini et al., 2012). Covenant violations are also associated with positive turnarounds in borrower performance, consistent with the actions taken by the borrower in response to a violation being value-improving, on average (Nini et al., 2012; Ersahin et al., 2021).

2.2 Trend in Financial Covenant Violations

Figure 1 shows that the incidence of financial covenant violations among U.S. public firms fell roughly 70% between 1997 and 2019, with the fraction of firms reporting a violation (solid blue line) peaking at 18% during the 2001 recession and declining thereafter, except for a modest increase during the 2008 global financial crisis (GFC). By 2012, the violation rate flattens to around 5%, where it remains through 2019. The dashed red line shows that the rate of "new" violations – defined as the subset of violations in which the firm has not reported a violation in the previous four quarters – follows a similar pattern, falling from roughly 9% on average during the years 1997-2003 to less than 2% from 2012-2019.[6]

These findings are based on the universe of U.S. nonfinancial firm-quarter observations in Compustat from 1997 to 2019 that can be matched to a corresponding 10-Q or 10-K SEC filing in EDGAR. We collect covenant violations reported in these filings using a text-search algorithm and manual inspection, as in Nini et al. (2012), and extend their original 1997-2008 dataset

[6] Following Nini et al. (2012), we focus on new violations in our subsequent analyses to cleanly identify the initial onset of enhanced creditor control and to cleanly measure contractual changes attributable to a given violation. As we describe more in Section 3.1, the sample of new violations is restricted to the subset of firm-year observations that have a loan outstanding with covenant and lender data available in Dealscan.

through 2019.[7] SEC and FASB reporting requirements allow us to identify all covenant violations regardless of whether they are outstanding or have been cured by a waiver. In our inspection process, we frequently find cases where a firm reports that their lenders agreed to waive an actual or impending covenant breach, and code these as violations.[8]

As in Nini et al. (2012), we require non-missing data on total assets, total sales, common shares outstanding, closing share price, and calendar quarter of the observation, and drop firms with average book assets of less than $10 million in real 2000 dollars. These filters yield an initial sample of 337,843 firm-quarters. We then aggregate to the firm-year level to minimize problems associated with quarterly variation in reporting quality.[9] To do so, we create an annual violation indicator for each firm-year that equals one when a firm reports a violation during any of the four quarters of the calendar year. The resulting sample consists of 85,876 firm-year observations from 9,618 U.S. nonfinancial firms between 1997 and 2019.

To ensure that the downward trend in violations is not due to biases in our data collection procedure, we conduct three robustness exercises and report the results in Appendix 1. First, we consider two independent violation measures: SEC reported violations from Roberts and Sufi (2009a) and Dealscan-Compustat imputed violations from Chava and Roberts (2008). Both measures confirm the strong drop in violations over time. Second, we assess whether firms have become better at manipulating their accounting ratios to avoid violations and find no evidence of

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[7] Regulation S-X requires "any breach of covenant …, which … existed at the date of the most recent balance sheet being filed and which has not been subsequently cured, [to] be stated in the notes to the financial statements" (CFR § 210.4-08). Further, "[i]f a default or breach exists but … has been waived for a stated period of time beyond the date of the most recent balance sheet being filed, …" Regulation S-X requires the firm to "… state the amount of the obligation and the period of the waiver" (CFR § 210.4-08).
[8] For example, Orion Group Holdings reported in a 10-Q filed on May 9, 2019, "During the first quarter of 2019, the Company initiated discussions with the lead bank due to concerns that it would not be in compliance with financial covenants and executed the Sixth Amendment during May 2019." We code this example as a violation.
[9] As noted in Nini et al. (2012), firms report violations more frequently in 10-Ks than 10-Qs because firms often summarize the experience of the entire year in annual reports. Moreover, aggregating to the firm-year minimizes the likelihood that our coding procedure fails to identify a violation, since we would have to miss four consecutive quarters of a reported violation.

increased bunching of reported ratios around contractual thresholds. Finally, we consider whether loan parties have become more likely to renegotiate before violation and, using data from Dealscan, find no evidence that loan amendments have become more common over time.

2.3 Trend in Financial Covenants

We study the evolution of financial covenants in debt contracts using Dealscan data. Dealscan provides loan information at both the package and facility level. We conduct our analysis at the loan package level because covenants typically apply to all facilities within a loan agreement. We merge all loan packages with Compustat using an updated version of the Chava and Roberts (2008) link file and accounting data from the first quarter-end immediately after loan origination. To remain in our sample, a Dealscan-Compustat borrower must be a U.S. nonfinancial firm with average book assets greater than $10 million in 2000 dollars and have a fiscal quarter-end date that is within 100 days of the Dealscan loan origination date. We exclude any deal that is not a U.S. syndicated senior bank loan denominated in U.S. dollars, all non-completed deals, and deals with missing covenant or lender information. This process yields a loan sample of 17,724 packages issued to 5,258 U.S nonfinancial firms between 1997 and 2019.

Figure 2 shows that the decline in violations coincides with a shift in the use of financial covenants. Panel A reports the time series average number of financial covenants per package and the average amount of "slack" in the covenants that remain, where slack is defined as the distance in standard deviations between the stated covenant threshold and the underlying financial metric for the tightest covenant in the package, measured at loan origination. In the late 1990s, the average loan contained roughly 2.75 financial covenants with average slack of one-half of a standard deviation. The average number of covenants began a steady decline after 2000, with a small blip up during the GFC, settling in at just above 1.5 covenants by 2016. Meanwhile, the tightest remaining covenant had, on average, three times as much slack in the latter years of the sample, compared to the late 1990s.

To summarize in one statistic the changes over time in the number and slack of financial covenants, we compute the Murfin (2012) measure of ex ante strictness using the updated methodology proposed by Demerjian and Owens (2016). This measure, commonly referred to as the "probability of violation", is based on the loan's financial covenant thresholds, the borrower's level of financial ratios at loan origination, and nonparametric simulations estimating whether a ratio will exceed its threshold. Panel B of Figure 2 shows that average covenant strictness fell by roughly half over our sample period, tracking the patterns in Panel A and Figure 1. The similarities in the time series pattern of ex ante strictness and ex post violations confirm that the design of financial covenants has undergone a substantial change over the last two decades.

3 Conceptual Framework for Covenant Design

To introduce our conceptual framework for covenant design, we draw an analogy between financial covenants and medical diagnostics. The goal of a medical test is to detect disease. In the event of a positive test for a disease, further testing is frequently required to confirm a diagnosis and develop a plan for treatment. Because medical tests often provide only a probabilistic assessment of the presence of disease, some truly diseased patients may produce a negative test, a mistake termed a "false negative." Financial covenants function similarly; they are tests applied periodically to assess the credit condition of the borrower. A positive outcome to a test (a violation), prompts further tests (additional monitoring) in which the lenders gather more information, diagnose the borrower's true credit health, and propose a treatment if needed. Because the performance ratios used in financial covenants are only imperfectly correlated with true distress, looser covenants can result in more false negatives, in which the covenants fail to catch borrowers that are truly distressed and require treatment.

Following a positive medical test result, subsequent testing sometimes reveals that the patient does not have the disease and requires no treatment, so the test result was a "false positive."

Financial covenants can also catch borrowers that are not distressed, as further monitoring reveals the borrower to be relatively healthy, requiring no further action other than a waiver. If violation-induced monitoring and renegotiation are costly, lenders will have an incentive to avoid setting covenants so tight that they trigger excessive false positives.[10]

We propose that the optimal contract balances these considerations, and loan parties have an incentive to design financial covenants that better detect when firms are truly financially distressed. Before formalizing the model in Section 3.3, we first explain our measurement of false positives and false negatives and discuss their costs.

3.1 Measuring False Positives and False Negatives

Our initial firm-year data splits observations into violators and non-violators, which we complement with a measure of firm-year distress. Conceptually, we consider a firm to be distressed if lenders would choose, if given the opportunity, to renegotiate a lending arrangement to protect their interests against a borrower whose credit risk is increasing. For firms violating a covenant, we measure distress directly by tracking loan amendments filed after the violation. Specifically, for each new violation, we read through the SEC filing that disclosed the violation, including attached exhibits, to determine how the violation was resolved.[11] We record whether the violation resulted in a change to the lending arrangement that: (i) raised the interest rate, (ii) reduced the loan commitment, (iii) required repayment of outstanding loan balances, or (iv) forced an asset sale or capital raising. We refer to violations with at least one of these four

[10] We take the existence of financial covenants as prima facie evidence of the costs of renegotiation. Instead of financial covenants that occasionally trigger renegotiation, loan agreements could have very short maturities that would trigger more frequent renegotiation. We take the ubiquity of long maturities and financial covenants as support for our assumption that renegotiation costs are important. Moreover, it is standard to assume that lenders engage in costly screening activities at loan origination, and renegotiating after a covenant violation involves very similar tasks.
[11] We restrict the sample to the subset of firm-years that have data available in Dealscan. This sample restriction cuts the full sample by about one-half, reducing the cost of data collection. Figure 1 shows that the time-series pattern of new covenant violations in this subsample mimics the pattern for the larger set of Compustat firms, suggesting that the analysis sample is representative of the overall population.

outcomes as "consequential" and label them as true positives.[12] We label all remaining violations – those that were waived without a consequential change to the lending arrangement – as false positives under the assumption that lenders determined that the borrower's credit quality had not deteriorated sufficiently to require a substantial change to the contract.

To provide some evidence in support of our classification system, we compare observable measures of credit risk between violating firms classified as distressed and non-distressed. On average, firms classified as false positives have lower book leverage (0.32 vs 0.41), higher cash holdings-to-assets (0.09 vs 0.06), and higher market-to-book (1.4 vs 1.2) than true positives in the quarter that they report a violation. The average false positive violator also has positive operating cash flow-to-assets (0.004) while the average true positive has a negative value (-0.005). Difference-in-means *t*-tests for these financial ratios are all significant at the 1% level, suggesting that covenants sometimes catch firms in relatively good financial health and lenders choose no treatment following the violation.

To distinguish between true and false negatives, we must infer times at which lenders to non-violating firms would have chosen to step in and renegotiate their lending arrangement if they were given the opportunity. This necessarily requires some judgment. As our primary measure, we rely on subsequent bankruptcy filings as a proxy of financial distress under the assumption that lenders would have renegotiated the loan terms for these firms to attempt to preclude the default or mitigate the costs associated with the default.[13] Accordingly, we code a firm that fails

[12] The range of actions that lenders can take after a violation is quite broad, so the four we code are not an exhaustive list. However, we believe the lack of one of these outcomes is a good indicator that the firm faced no other serious consequences. In our reading of SEC filings for violators, we observed no cases in which a reasonable reading of the outcome would suggest that the firm faced adverse consequences while avoiding all four outcomes we code. For this reason, we believe that our classification of false positives is measured with very little error.

[13] To best identify bankruptcies, we combine bankruptcy data from Compustat, CRSP, Audit Analytics, and the UCLA-LoPucki Bankruptcy Research Database. We verify each Compustat and CRSP bankruptcy by hand-collecting filing dates because these data providers only offer deletion and delisting dates, respectively, which do not perfectly correspond to bankruptcy filings. The one-year horizon is somewhat arbitrary, but we believe it is a reasonable period for covenants to serve as an early warning signal.

to violate a covenant but files for bankruptcy within one year as a false negative and all other non-violators as true negatives. We examine the robustness of our results using three alternative approaches to measure distress for non-violators. The first strategy classifies a firm as distressed if its estimated probability of default is in the upper fifth percentile of the empirical distribution of default probabilities according to the according default model in Bharath and Shumway (2008). The second strategy classifies a firm as distressed if it receives a "going concern" warning from its auditors. Third, we extend the horizon for a bankruptcy filing from one year to five years. Internet Appendix Figure IA.1 shows that these measures display similar time series patterns.

Figure 3 presents a 2 x 2 classification of our sample into false positives, true positives, false negatives, and true negatives. The matrix shows that 93.6% of firm-years are classified as true negatives, reflecting the fact that relatively few firms violate financial covenants and non-violators rarely experience distress. True positives and false positives represent 2.5% and 2.9% of the sample, respectively, meaning that more than half of violations are waived with no consequential change to the lending arrangement.[14] False negatives represent 1.1% of the sample. While this percentage is small relative to the overall sample, false negatives represent about 30% of the distressed firms in our sample.

3.2 The Cost of False Negatives and False Positives

The downward trend in financial covenant violations could reflect an increase in false negatives, which would imply that lenders have fewer opportunities to intervene early during periods of distress. Prior research shows that delaying a creditor intervention can increase

[14] For comparison, Chen and Wei (1993) find that 45% of the 128 violations that they analyze from 1985 to 1988 were waived with no additional changes to loan terms, and Chodorow-Reich and Falato (2021) show that, during the 2008 financial crisis, only 37% of firms faced a reduction in their credit line following a violation. Bird, Ertan, Karolyi, and Ruchti (2022) estimate that lenders enforce only 11% of covenant breaches based on the slack between Dealscan thresholds and Compustat values; however, Dyreng, Ferracuti, Hills, and Kubic (2022) caution that the Bird, Ertan, Karolyi, Ruchti (2022) finding may be driven by measurement error in slack data that overestimates the occurrence of breaches.

financial distress costs because incentives are better aligned between equityholders and debtholders when a company is distressed but still profitable (Francois and Morellec, 2004; Carey and Gordy, 2021), because stepping in earlier allows for better coordination and planning between the company and creditors (Ivashina, Iverson, and Smith, 2015), and because excess delay can increase deadweight bankruptcy costs (Dou, Taylor, Wang, and Wang, 2021).

We directly estimate the cost of a false negative by observing the impact of false negatives on creditor recovery rates of defaulted firms. To construct the sample, we begin with the 826 bankruptcies in Moody's Ultimate Recovery Database (URD) between 1997 and 2020 and merge the cases with our covenant violation sample using the borrower's CUSIP, name, and ticker.[15] We then visually inspect each match to assure accuracy. This process yields a sample of 403 bankruptcies with complete data. Roughly one-half reported a financial covenant violation in the year prior to bankruptcy; the remaining one-half reported no covenant violation prior to the bankruptcy filing. We study firm-level recovery rates – computed as the par value-weighted average of the recovery rates for the firm's obligations – as a measure of the total losses born by creditors of the bankrupt firm.

Table 1 reports regression estimates of firm-level recovery rates on a No Violation indicator that equals one if the firm did not report a financial covenant violation in the year before bankruptcy. Column (1) shows that recovery rates are 11.4 percentage points lower, on average, for firms that do not report a covenant violation prior to bankruptcy. This coefficient estimate remains stable at around 10 percentage points when we include year and industry fixed effects in Column (2) and add more borrower controls in Column (3). In Column (4), we add Bank Debt

[15] According to Moody's, the URD contains the most robust set of recovery data commercially available because their analysts read through all necessary court documents and SEC filings and rely on years of experience to accurately calculate recovery pricing. Moody's calculates the amount of money recovered for each instrument based on settlement, liquidation, or open market trading prices, and discounts on a dollar basis for lost interest. The database covers defaults by U.S. nonfinancial firms with at least $50 million in debt and focuses primarily on rated borrowers.

Share, defined as the fraction of pre-bankruptcy debt consisting of revolvers and term loans, which Carey and Gordy (2021) find is a strong determinant of firm recovery rates. Column (4) shows that while Bank Debt Share is a strong predictor of recovery rates, the No Violation coefficient remains negative and significant.

The results in Table 1 imply that false negatives are costly at the firm level, representing a loss of roughly 10 percentage points in value to creditors of bankrupt firms that do not violate a covenant prior to the default. Based on data from 1997-2020, the average firm-level recovery rates in Moody's URD was 54% of par value, so the Table 1 estimates imply that creditors of non-violating firms suffer roughly 20% greater losses in bankruptcy, on average, compared to violating firms. As an alternative comparison, Mora (2012) reports that, over the period from 1970 to 2010, firm-level recovery rates were 7 percentage points lower, on average, in recessions than during expansions. If the trend toward looser covenants reflects substantially more false negatives, the 10-percentage point average loss on defaulted firms could translate to larger aggregate losses to lender, particularly during periods of high default.

The downward trend in financial covenant violations could also reflect a decrease in false positives, which would imply that loan parties experience fewer nuisance violations which are potentially costly. A false positive is potentially costly for at least two reasons. First, the renegotiation following a violation creates costs associated with monitoring the borrower, amending the loan contract, and coordinating lender groups. A growing literature stresses that these renegotiation costs are substantial enough to become an important consideration in the design of lending arrangements, particularly for dispersed institutional lenders (e.g., Demiroglu and James, 2015; Becker and Ivashina, 2016; Berlin, Nini, and Yu, 2020). Second, because a violation grants lenders considerable bargaining power during an ensuing renegotiation, there is scope for lenders to hold up borrowers. For example, Chodorow-Reich and Falato (2022) show that lenders in worse health during the GFC were more likely to reduce the size of loan commitments following a covenant violation – even for healthy borrowers – than lenders less impacted by the crisis. To the extent that the trend toward looser covenants reduces costly false positives, the downward trend in violations could reflect an aggregate economic benefit, including to the financial sector.

3.3 A Model of Financial Covenant Thresholds

To model optimal covenant design, we assume that the population of borrowers contains non-distressed and distressed firms, denoted $\widetilde{D} = \{0,1\}$. The lender cannot perfectly observe the borrower's status but can write covenants on a set of financial metrics correlated with the true status. Adopting the notation of Murfin (2012), we refer to the financial metric as r, the contractual threshold as t, and denote a violation as $\tilde{V} = \{0,1\}$. A violation occurs if $r > t$. Because observable metrics detect distress imperfectly, covenants create two statistical classification errors. First, a covenant may fail to catch a distressed firm – a false negative outcome – with probability $\Pr(V = 0, D = 1)$. Second, a covenant may catch a non-distressed firm – a false positive – with probability $\Pr(V = 1, D = 0)$. We denote the cost of these errors as C_{FN} and C_{FP}, respectively.

Distressed and non-distressed firms have different distributions over r such that $\Pr(r < t|D = 1) = F_D(t)$ and $\Pr(r < t|D = 0) = F_{ND}(t)$. The distribution functions determine the false negative rate (FNR) and false positive rate (FPR), respectively, which are the conditional probabilities of misclassification: $\text{FNR}(t) = \Pr(r < t|D = 1) = F_D(t)$ and $\text{FPR}(t) = \Pr(r > t|D = 0) = 1 - F_{ND}(t)$. Because $\text{FNR}(t)$ is increasing in t and $\text{FPR}(t)$ is decreasing in t, loan parties face a trade-off when setting the covenant threshold. A tighter threshold results in a lower probability of a false negative but a higher probability of a false positive. We illustrate the tradeoff in Figure 4 by plotting a receiver operating characteristic (ROC) curve, which is a graph of the relationship between the test's TPR and FPR, where TPR =

$(1 - \text{FNR})$. The figure displays ROC curves for two different tests, along with a 45-degree line that represents an uninformative test. The ROC curve that pushes further away from the 45-degree line represents a better test, in that it better discriminates between distressed and non-distressed borrowers. We refer to a better test as better covenant "technology," since the test allows for a lower level of the FPR for any given TPR.

A natural objective is to assume the optimal covenant threshold is set to minimize the total expected costs of false positives and false negatives,

$$(1 - \bar{\rho})FPR(t)C_{FP} + \bar{\rho}[FNR(t)]C_{FN},$$

where $\bar{\rho}$ is the unconditional probability that a firm is distressed. The first-order condition for the minimization problem yields an intuitive equation that determines the optimal threshold:

$$\frac{(1-\bar{\rho})}{\bar{\rho}} \frac{C_{FP}}{C_{FN}} = \frac{f_D(t^*)}{f_{ND}(t^*)}, \tag{1}$$

where $f_D(\cdot)$ and $f_{ND}(\cdot)$ are density functions corresponding to $F_D(\cdot)$ and $F_{ND}(\cdot)$. The left-hand side of (1) is the ratio of expected costs of false positives to false negatives, which we refer to as the loan party "preferences." We expect $\frac{C_{FP}}{C_{FN}}$ to be much less than 1 and $\frac{(1-\bar{\rho})}{\bar{\rho}}$ to be much larger than 1. The right-hand side of (1) is a likelihood ratio for the relative probabilities of violation for a distressed and non-distressed borrower and is the slope of the ROC curve at the optimal threshold t^*. At the optimal threshold, the updated odds that the violating borrower is distressed equals the ratio of expected costs of false positives to false negatives.

The covenant technology determines the set of FPR, TPR combinations that are possible, and the optimal choice depends on the preferences of the loan parties. Because the optimal threshold is increasing in the preference parameter, $\frac{(1-\bar{\rho})}{\bar{\rho}} \frac{C_{FP}}{C_{FN}}$, an increase in the expected costs of false positives, $(1 - \bar{\rho})C_{FP}$, relative to the expected costs of false negatives, $\bar{\rho}C_{FN}$, will cause the optimal threshold to become looser. In Figure 4, this scenario is represented by the movement from Point 1 to Point 2 along a constant ROC curve. Conversely, if the technology improves to allow better discrimination between distressed and non-distressed borrowers, covenants will adjust to generate a lower FPR and a higher TPR. In Figure 4, this scenario is represented by the shift from Point 1 to Point 3 on a different ROC curve.

The logic of the model delivers the following potential explanations for the observed downward trend in covenant violations through time:

1. *A lower relative cost of a false negative*, perhaps driven by elevated financial market sentiment that erodes credit standards. Such a change would loosen the optimal threshold, leading to a lower FPR, TPR, and covenant violation rate.
2. *A higher relative cost of a false positive*, perhaps driven by a shift in the composition of lenders. This would loosen the optimal threshold, leading to a lower FPR, TPR, and violation rate.
3. *A lower prevalence of distress*, perhaps driven by a shift in the composition of borrowers. This would loosen the optimal threshold, leading to a lower FPR, TPR, and violation rate.
4. *An improved ability to discriminate between distressed and non-distressed borrowers* caused by an improvement in covenant technology. This would lead to a lower FPR and a higher TPR and a potential drop in the violation rate.

4 Assessment of the Trend in Violations

We begin this section with an empirical decomposition of the annual covenant violation rate into the distress rate, TPR, and FPR, and an analysis of how these components change over our 23-year sample period. We then use the decompositions to estimate structural parameters derived from our model of optimal covenant design. The decomposition and structural estimates yield insight into the fundamental drivers behind the trend in covenant violations.

4.1 Empirical Decomposition

Applying the statistical classification as in Figure 3, we can decompose the violation rate in any year t using the following identity:

$$V_t = \rho_t \cdot TPR_t + (1 - \rho_t) \cdot FPR_t, \tag{2}$$

where V_t is the annual rate of covenant violations, ρ_t is the realized distress rate ($\rho_t = \frac{FN_t + TP_t}{N_t}$), TPR_t is the realized true positive rate ($TPR_t = \frac{TP_t}{TP_t + FN_t}$), and FPR_t is the realized false positive ($FPR_t = \frac{FP_t}{FP_t + TN_t}$). Figure 5 displays the time series of each of the three rates along with the estimated 95% confidence interval for the proportions.

Panel A of Figure 5 shows that the realized rate of distress is cyclical, with peaks during the business cycle contractions in 2001 and 2008. But over the entire period, the distress rate trends downward, with the rate between 2010 and 2019 remaining at or below the rate experienced from 1997 to 2009. Panel B shows that the rate of false positives has dropped steadily and dramatically from a level of about 6% in the late 1990s to less than 0.5% in 2019. Panel C shows that the TPR remained roughly constant through 2011 and declined following the GFC. Between 1997 and 2011, roughly 75% of distressed firms were "caught" by a covenant violation prior to default. Over the period 2012-2019, the TPR fell to around 50%, on average, implying that the false negative rate – in which distressed firms fail to violate a covenant – increased from 25% during 1997-2011 to 50% firms in the latter part of the sample. Figures IA.2.-IA.4 in the Internet Appendix show that the patterns in Figure 5 are robust to alternative measures of the distress rate.

Equation (2) allows us to quantify the relative contribution of the distress rate, the TPR, and the FPR to the overall fall in realized violations. We decompose the change in the violation rate from year s to year t as:

$$\Delta V_{s,t} = V_t - V_s = \underbrace{\rho_s(\Delta TPR)}_{\text{"TPR"}} + \underbrace{(1 - \rho_s)(\Delta FPR)}_{\text{"FPR"}} + \underbrace{(TPR_t - FPR_t)(\Delta \rho)}_{\text{"Distress"}} \tag{2}$$

where $\Delta TPR = TPR_t - TPR_s$, $\Delta FPR = FPR_t - FPR_s$, and $\Delta \rho = \rho_t - \rho_s$.

Table 2 reports the decomposition across three subperiods (represented as vertical lines in

Figure 5): 1997-2003, 2004-2011, and 2012-2019. The subperiods are roughly equal in length and correspond to three different regimes for the combinations of TPR and FPR that overlap with, respectively, credit cycles associated with (1) the "dot-com" era, (2) the period up to, and including, the GFC, and (3) the period of extended recovery following the crisis before the COVID pandemic. Panel A of Table 2 reports averages for the realized violation rate, distress rate, FPR, and TPR over each of the subperiods and confirms, for example, that the violation rate fell by about 85% from the first period to the third period. The distress rate, FPR, and TPR, decline in a manner consistent with the graphs shown in Figure 5.

Panel B of Table 2 reports the contribution of each factor to the change in the violation rate between the periods. Between periods 1 and 2, the 4.6 percentage point reduction in violations is entirely attributable to a combination of the decline in distress, which explains 1.8 percentage points – or 39% – of the observed drop in violations, and the fall in the FPR, which explains 2.9 percentage points – or 63% of the decline. Because the TPR increased slightly between the first two periods, its effect is to reduce the violation rate by 0.1 percentage points. In sum, the observed downward trend in violations during the early part of the sample can be explained entirely by a falling rate of distress among public companies and a drop in false positives. During this period, we observe no decline in the ability of financial covenants to catch distressed borrowers early, even as conventional measures of covenant strictness showed a marked loosening (see Figure 2).

Panel B also shows that the additional 2.9 percentage point drop in violations between periods 2 and 3 is mainly attributable to a fall in distress and a continued decline in the FPR. Between periods 2 and 3, the fall in distress explains 0.6 percentage points (20%) and the decline in the FPR explains 1.7 percentage points (57%) of the drop in violations. In contrast to the 2004-2011 period over which the TPR increased slightly, the TPR drops during 2012-2019 by over 20 percentage points. This decline in the TPR explains the remaining 0.7 percentage points (23%) of the decline in violations during period 3. The drop in the TPR suggests that the ability of covenants to catch distressed borrowers worsened during this period.

Tables IA.1.-IA.3. of the Internet Appendix reproduce Table 2 using three other measures of distress. The relative contributions of the distress rate, the TPR, and the FPR to the overall fall in violations reported in the Internet Appendix closely match results reported in Table 2, Panel B.

The decomposition in Panel B of Table 2 provides some perspective on the economic implications of the decline in covenant violations. Over the full sample period, the steep drop in the FPR explains most (61%) of the 7.6 percentage-point fall in violations. To the extent that false positives involve costly monitoring and renegotiation, the sharp drop in the FPR implies that loan parties have benefited from cost savings as the violation rate has dropped. The downward trend in distress explains another 25% of the decline in violations. Only about 14% of the decline in violations over the 23-year period derives from a drop in the TPR that occurs during the last subperiod. Even if the TPR rate had remained at 75% over the entire sample period, the violation rate still would have dropped from 8.9% at the start to 1.8% at the end of the period, which is only slightly higher than the realized 1.3%.[16]

4.2 Aggregate Costs of False Negatives

Although the fall in the TPR explains only a small fraction of the overall trend in violations, it does indicate an increase in false negatives, particularly during 2012-2019. False negatives lead to lower recovery rates for firms in bankruptcy, and their aggregate cost will depend on the fraction of bankruptcies that are false negatives. From 1997 to 2003, the TPR was 72.3% and the fraction of false negatives in our sample of bankruptcies was 42%. Assuming a 10% loss per false negative bankruptcy (per the estimates in Table 1), the average recovery rate during the 1997-2003 period was about 4.2% lower than a counterfactual world without any false negatives.

[16] To see this, note that $1.8\% = +1.8\% \cdot 75\% + (1 - 1.8\%) \cdot 0.5\%$.

During the 2012-2019 period, however, the TPR fell to 51.5% and the fraction of false negative bankruptcies increased to 75%, so the estimated impact on the average recovery rate increases to 7.5%. Comparing across periods, we estimate that the average recovery rate was 3.3 percentage points lower due to the change in lending standards during the latter years of the sample, which is about one-half of the 7-percentage point impact of recessions estimated by Mora (2012).

We can also consider how false negative outcomes affect an aggregate portfolio of loans, accounting for the fact that only a small fraction of firms will go bankrupt. In our sample, the distress rate is 5.4% during 1997-2003 so, assuming conservatively that all distressed firms go bankrupt, the aggregate impact of false negatives would be 23 basis points ($0.054 \cdot 0.042 = 0.0023$) of extra losses relative to the aggregate portfolio of loans. During the 2012-2019 period, the distress rate is only 1.8% so the estimated impact of the lower TPR falls to 14 basis points ($0.018 \cdot 0.075 = 0.0014$), which is small relative to the average loan spread of 190 basis points in the sample from Section 2.3. Of course, the low distress rate in recent years may not be representative of future bankruptcy rates, particularly during an economic downturn, so the impact of a low TPR could be larger in the future. For example, if three-quarters of bankrupt firms remain false negatives, a bankruptcy rate of 10% – a level seen among speculative-grade firms only at the peaks of the dot com bust and GFC – would increase the expected cost of false negatives to 75 basis points.

4.3 Estimating Structural Parameters

We next use the realized FPR and TPR to extract estimates of the parameters from equation (1) that govern the optimal choice of covenants. We assume that the performance metric has a normal distribution that depends on the status of the firm; $r \sim N(\mu_D, 1)$ for distressed firms and

$r \sim N(0,1)$ for non-distressed firms.[17] The parameter μ_D provides a measure of the covenant "technology", with a higher μ_D indicating better technology. We first estimate t^* – the optimal covenant threshold – using the realized FPR and the relationship $\text{FPR} = 1 - \Phi(t^*)$, where $\Phi(\cdot)$ denotes the standard normal CDF. Next, we estimate μ_D using the equation $\text{TPR} = 1 - \Phi(t^*;\ \mu_D)$, where $\Phi(\cdot;\ \mu_D)$ denotes the normal CDF with mean μ_D. With an estimate of μ_D, we can trace out an estimated ROC curve by computing implied TPRs and FPRs for alternative thresholds. Finally, we use equation (1) to estimate the ratio of expected costs of false positives to false negatives, which we denote as R. We estimate R using the assumption of a normally distributed performance metric, which generates an ROC curve with a slope of $e^{\frac{[(2t^* - \mu_D)(\mu_D)]}{2}} = R$. Because the parameter estimates are functions of sample statistics with known sampling variances, we can use the delta method to estimate the standard errors of the model parameters. Table 3 provides estimates of the structural parameters across our three subsample periods, while Figure 6 illustrates the findings using the estimated ROC curves and points from the actual FPR, TPR outcomes realized in each of the subperiods.

The covenant technology parameter, μ_D, in Panel A of Table 3 increases from a level of 2.21 between 1997-2003 to 2.68 in 2004-2011, a change that is statistically significant at the 5% level. The technology parameter then drops slightly to 2.65 during the latter period, 2012-2019, although the estimate is not statistically different from the 2004-2011 period. Figure 6 shows the improvement in covenant technology as movement out to the left in the ROC curves for the second two subperiods. The ROC curve shows that, for a given level of the TPR, the improved covenant technology permits a meaningfully lower FPR.

To measure the economic importance of the increase in covenant technology, Panel B in Table

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[17] We assume a variance of 1 because the variance of the distribution is unidentified. Since the TPR and FPR are proportions, we can estimate either the threshold or the variance, as in a probit model for a binary outcome. We normalize the variance to unity and estimate the threshold.

3 reports the results of a counterfactual exercise in which we hold preferences at their 1997-2003 level and recalculate changes in the FPR, TPR, and violation rate according to the model. Panel B shows that improvements in covenant technology alone would have resulted in a drop in the violation rate of 3.5 percentage points to 5.4% by the end of the sample period, compared to the actual drop to 1.4%. This outcome is identified in Figure 6 as the 'X' on the graph, which shows the counterfactual FPR, TPR outcomes that would have prevailed in 2012-2019 holding *R* at the 1997-2003 level. Improvements in covenant technology would lead to optimally looser covenants, allowing a higher TPR and a lower FPR. In Section 5, we examine the rapid shift away from the use of balance-sheet metrics as financial covenants in favor of cash-flow based covenants as a potential driver of the improvement of covenant technology.

Although technology improved over the sample period, we estimate a substantially larger change over time in the relative expected costs of false positives to false negatives. The estimate of *R* nearly doubles between 1997-2003 and 2004-2011, from 3.10 to 6.06, and then increases nearly five-fold to 30.29 during 2012-2019. These changes are shown in Figure 6 by the movement of the realized FPR, TPR values to the lower left along the ROC curves. Panel B of Table 3 emphasizes the impact of the large increase in *R* by holding technology fixed and computing the counterfactual violation rate due solely to changes in preferences. Holding technology constant, the increasing values of *R* drive down both the FPR and the TPR, so that by the end of the sample period, the TPR falls by more than half, from 72.3% to 33.0%. The reduction in the TPR is noteworthy because it implies that, holding technology constant, market participants would tolerate covenants so loose that the covenants would miss nearly seven of 10 firms that become financially distressed. Figure 6 marks this counterfactual outcome with the '+', calculated assuming that the covenant technology remained at its 1997-2003 level. Using the realized level of distress in 2012-2019, the counterfactual FPRs and TPRs would have yielded a violation rate of 1.0%, which is below the observed 1.4%.

The structural estimates provided in Table 3 and Figure 6 allow us to explain how the trends documented in Figure 5 are related to changes in underlying fundamentals. Between 1997-2003 and 2004-2011, the FPR falls significantly despite a small increase in the TPR. The model explains this change as an improvement in covenant technology – which permits the FPR to fall without much increase in the TPR – coupled with an increased willingness to accept more false negatives in exchange for fewer false positives. Because, as shown in Figure 6, our functional form assumption yields a fairly flat ROC curve in the range relevant for the earlier sample period, even a large change in preferences results in only a relatively small decrease in the TPR. Between 2004-2011 and 2012-2019, however, the TPR drops appreciably. Given that the realized combination of TPR and FPR is nearly exactly what would be predicted from the 2004-2011 ROC curve, our model attributes the change entirely to a shift in preferences. The change in preferences, as manifested in the estimates of R, could arise due to a variety of factors, including elevated investor sentiment that could raise concerns about financial stability or other developments in the corporate loan market. In the next section, we work to tease out these explanations by examining how changing market characteristics explain these trends.

5 The Role of Changing Loan Market Characteristics

Thus far in our analysis, we have implicitly treated the sample of public borrowing firms and lenders as static over the 23-year sample period. However, the syndicated loan market changed substantially between 1997 and 2019, and these changes could explain at least part of the observed trends. The number of U.S. publicly listed companies declined by half over the sample period (Doidge, Karolyi, and Stulz, 2017) and the typical firm at the end of our sample is larger, older, and financially healthier than the average firm at the start of the period (Kahle and Stulz, 2017). To the extent that larger borrowers have always carried lighter covenant packages and violated covenants less often, the observed drop in violations could reflect the changing composition of publicly traded firms during our sample period. Meanwhile, the nature of loan arrangers and syndicate participants has also evolved over time, coincident with leveraged loans becoming more "covenant lite" (Becker and Ivashina, 2016; Berlin et al., 2020).

In this section, we first examine the evolution of borrower and lender characteristics in our sample and assess the relation between these characteristics and covenant design. We then use the characteristics as regressors in a Blinder-Oaxaca decomposition to examine how much of the TPR, FPR, and total trend in violations can be explained by observable changes in the market.

5.1 Loan Market Composition and Covenant Design

We begin by examining trends in covenant design across samples split by borrower characteristics. In panel A of Figure 7, we zoom in on the largest and smallest quartiles of firms, based on total assets (in real 2000 dollars), and in panel B, we split the sample into firms with an investment grade rating (from S&P), speculative grade rating, or that are unrated. The left panels in Figure 7 depict the changes in sample composition, and the right panels plot the time series of average covenant strictness for the size and rating splits.

Consistent with the findings in Kahle and Stulz (2017), the left graph in Panel A of Figure 7 shows that the size of the borrowers in our sample of public firms has increased over time. The proportion of firms in the smallest quartile has dropped from roughly half of the sample in 1997 to less than 10% by 2019, while the largest quartile has come to dominate the sample, growing from 10% to nearly 50% of the sample by 2019. This compositional change alone could influence the trends in covenant strictness and violations because, as shown in the right panel of Panel A of Figure 7, the loan agreements for larger borrowers have always had looser covenants than for smaller firms.

Likewise, Panel B of Figure 7 shows that the proportion of borrowers unrated by S&P has declined through time, consistent with larger borrowers being more likely to have a credit rating and with more borrowers choosing to be rated for a bank loan (Sufi, 2009). The fraction of firms with an investment-grade rating and the fraction with a speculative-grade rating have each increased from less than 20 percent of our sample to over 40 percent by the end of the period. The rise in firms with an investment-grade rating is particularly noteworthy since these firms have a very low probability of default and, as shown in the right graph in Panel B, considerably looser covenants. Like the impact of firm size, the growing dominance of investment-grade firms in our sample could contribute to the observed decrease in covenant violations over time.

Figure 8 provides a similar analysis based on changing lender characteristics. In Panel A, we split loans based on whether the loan arranger is a "universal bank", which we code based on the logic in Neuhann and Saidi (2018). Universal banks include international banks that have a U.S. investment bank division and U.S.-based institutions with both commercial and investment bank operations. Panel A shows that universal banks arranged more than 95 percent of loans by the end of our sample period, up from nearly 80 percent at the start. The remaining loans are arranged by non-universal commercial banks or nonbanks. Chen, Lee, Neuhann, and Saidi (2023) show that universal banks syndicate their loans more broadly across more participants, and the right-hand side of Panel A of Figure 8 shows that loans arranged by universal banks tend to have looser covenants, consistent with higher renegotiation costs among large syndicates.

Because Dealscan provides only limited information about syndicated lender participation (Blickle, Fleckenstein, Hillenbrand, and Saunders, 2020), we form a second proxy for lender identity based on whether the loan includes a tranche structured for the institutional market, as identified by Dealscan. Panel B of Figure 8 shows that the fraction of loans containing an institutional tranche peaked in the years prior to the GFC. It also shows loan packages that include an institutional tranche have greater ex ante covenant strictness, on average, likely because institutional investors participate mainly in the leveraged loan market (Berlin et al., 2020) and riskier borrowers have tighter covenant packages. Together, the evidence in Panel B of Figure 8 suggests that the growth of the institutional term loan market is unable to explain the overall change in covenants and violations in recent years. This evidence also suggests that the trend towards looser package-level financial covenants is a separate phenomenon from the rise of term loans facilities that are covenant-lite.

Figure 9 splits the sample according to whether the package of financial covenants contains only balance sheet measures of performance, including net worth, current ratios, and debt-to-equity and debt-to-asset ratios, or contains covenants that rely on cash flow measures of performance, such as debt-to-EBITDA and EBITDA "coverage" ratios (e.g., interest coverage or fixed charge ratios). Consistent with the findings first documented by Demerjian (2011), Figure 9 shows a discernible time-series shift away from balance sheet covenants in credit agreements of public borrowers. More than 15% of covenant packages relied on balance sheet measures in the late 1990s, but by the end of the sample, covenant packages composed only of balance-sheet financial covenants were practically non-existent. To the extent that cash-flow based covenants are more sensitive measures of borrower performance, a move to cash-flow based covenants would represent an improvement in technology that could allow financial covenants to be set looser without reducing their ability to catch distressed borrowers. Consistent with this logic, the right-hand panel shows that loan agreements using only balance sheet covenants are considerably stricter than packages using cash-flow covenants. Thus, the shift over time to cash-flow based covenants could also contribute to the downward trend in violations and, as we explore further in the next section, do so in a manner consistent with an improvement in covenant technology.

5.2 Blinder-Oaxaca Decomposition

We quantify the impact of the changes shown in Figures 7-9 on our estimates of the FPR and TPR using a decomposition in the style of Blinder (1973) and Oaxaca (1973). The Blinder-Oaxaca decomposition allows us to separate changes in the FPR and TPR into the components explained by the evolution in observable loan market characteristics and the components left unexplained by the characteristics.

To accomplish the decompositions of the FPR and TPR, we estimate two probit regressions that relate a covenant violation indicator to a set of characteristics measured at the time the firm last received a loan, so as to reflect the covenant technology and preferences at the time covenants were set. In the first regression, we limit the sample to firms that we classify as non-distressed to capture how the characteristics affect the FPR. The second regression includes only distressed firms and captures the impact of the characteristics on the TPR. The advantage of separating the sample into distressed and non-distressed firms is that the estimated coefficients can vary across the two groups, including having different signs. For example, characteristics, such as the move away from balance sheet covenants, could be associated with changing lending technologies, which would have a different impact on the direction of the TPR and FPR.

We begin by reporting regression results using the full 23-year period without any calendar-period fixed effects. These estimates can be interpreted as capturing the average mapping from the characteristics into the FPR and TPR across the full sample. We subsequently examine how changes over time in the characteristics – holding the mapping constant – can explain the realized trends in the FPR and the TPR.

Panel A in Table 4 reports the estimated marginal effects from the two probit regressions, and Panel B reports the mean level of the explanatory variables within each of the three subperiods. Consistent with the pattern observed in Figure 7, Borrower Size, measured as the logarithm of total assets in 2000 dollars, is significantly negatively related to both the FPR and TPR, indicating that preferences for looser covenants are stronger in loan packages to larger firms than smaller firms. This pattern could indicate that that larger firms have a lower unconditional probability of being distressed, that larger firms have a higher relative cost of false positives to false negatives, or some combination of both. Credit ratings have a mixed impact on the realized FPR and TPR. Firms with an investment-grade credit rating have a significantly lower FPR and a higher, though insignificant, TPR. Firms with a speculative-grade credit rating, however, have a lower TPR, so the increase in the latter part of the sample in firms with a speculative-grade rating could help explain the observed fall in the TPR over the same period.

The two variables representing lender characteristics have minimal impact on the realized FPR and TPR. Loans arranged by a universal bank, as opposed to a commercial bank or a nonbank, have lower FPR and higher TPR, although the indicator is only statistically significant in the FPR regression. We find no significant relationship between the indicator variable that flags institutional loans and the FPR or TPR. Given that prior research documents substantial matching between lenders and borrowers in the loan market, however, it is difficult to entirely separate borrower effects from lender effects. For example, large borrowers tend to raise debt from large banks (Berger, Miller, Petersen, Rajan, and Stein, 2005) and speculative grade borrowers are more likely to access the institutional loan market (Berlin et al., 2020).

Finally, we include an indicator equal to one if the loan contains only balance sheet covenants as opposed to using at least one cash flow covenant. The regression estimates show that Balance Sheet Covenant is positively related to the FPR and negatively related to the TPR, supporting the idea that balance sheet covenants represent worse covenant technology and an increase over time in the use of cash flow covenants has improved covenant technology. Notably, the decline in the use of balance sheet covenants between periods 1 and 2 coincides with the increase in the technology parameter, μ_D, observed in Table 3.

In Table 5, we formally assess the degree to which changes in these characteristics can explain the trend in violations using a Blinder-Oaxaca decomposition. Based on the coefficient estimates in Table 4, we decompose the change in the realized violation rates from period s to period t as:

$$\overline{Viol^{t}} - \overline{Viol^{s}} = \underbrace{\overline{\Phi\left(X^{t}\,\hat{\beta}\right)} - \overline{\Phi\left(X^{s}\,\hat{\beta}\right)}}_{\text{"Explained"}} + \underbrace{U}_{\text{"Unexplained"}} \tag{3}$$

where Φ denotes the standard normal CDF used in the Probit specification, $\hat{\beta}$ represents the coefficient estimates in Table 4, and X is the set the explanatory variables used in the regression. The overbar reflects a sample average, which we compute using observations from the relevant period. The "Explained" portion of equation (3) captures the impact of changes in the distribution of values of the variables in X, using a constant mapping from the variables into violation status. The variable U is the "Unexplained" portion of the change, which captures changes in sample characteristics beyond the variables in X or changes in the mapping from X to violation status, or both. Although a similar decomposition could allow the Probit parameter estimates to vary by period, such an approach would not inform us why the mapping changed, so we prefer the simpler decomposition that leaves everything not explained by changes in the sample as unexplained. We use the method from Yun (2005) to attribute the explained portion of the overall change to individual explanatory variables and estimate standard errors by the delta method.

Table 5 reports the results of the decomposition between periods 1 and 2 and between periods 1 and 3. The top panel shows that a large portion of the trend in the FPR and TPR can be explained by changes in observables. Between periods 1 and 2, nearly one-half of the fall in the FPR (1.5 percentage points out of 3.1 percentage points) can be explained by changes in the observable characteristics, particularly the large increase in the size of borrowers, which by itself contributes 1.35 percentage points to the downward trend in the FPR. Similarly, the explained portion of the change between periods 1 and 3 is more than one-half of the total change, with Borrower Size again providing a substantial contribution to the fall in the FPR. The rise of firms with an investment-grade rating and the growth of universal banks also contribute modestly to the fall in the FPR.

Between periods 1 and 2, the TPR does not change significantly, but the decomposition shows that changes in characteristics contribute to a statistically significant 3.0% fall in the TPR. In particular, the table shows that increases in Borrower Size and Speculative-Grade Rating – which Table 4 shows are both negatively correlated with the TPR – pushed down the realized TPR, as the tilt through time towards bigger and riskier-rated firms has had a negative impact on the realized TPR. This decline is partially offset by a 1.2 percentage point *increase* in the TPR between periods 1 and 2 associated with the decreased prevalence of balance sheet covenants. This observed improvement in covenant technology explains, in part, the increase in the technology parameter, μ_D, between periods 1 and 2, as shown in Table 3 and Figure 6. Meanwhile, the unexplained portions of the changes from period 1 to 2 show that the FPR falls while the TPR increases, indicating that features beyond the use of cash-flow covenants contributed to improvements in covenant technology over these periods.

As shown earlier, the TPR drops markedly during period 3. Table 5 shows that a large portion of this drop – 60% – can be explained by changes in the characteristics. Borrower Size and Speculative-Grade Rating are again the major drivers of the drop in the explained TPR, cumulatively accounting for more than 10 percentage points of the drop in the TPR between periods 1 and 3. The decline in balance sheet covenants continues to offset the decline in the TPR, but its cumulative impact becomes small in the face of the large declines in the TPR caused by the increases in borrower size and speculative grade borrowers.[18]

5.3 Observable Characteristics and the Trend in Violations

We summarize the decomposition exercise by computing the violation rate implied by the explained portion of the FPR and TPR. These counterfactual values of the FPR and TPR, reported in the first two columns of Table 6, are computed as the actual values in period 1 plus the explained portion of the change reported in Table 5.[19] These values represent our best estimates of the FPR and TPR that would have prevailed exclusively due to the changes in the regressors used in Table 4. We compute the predicted violation rate using the realized default rate and equation (2) and report the results in the third column of Table 6.

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[18] In addition to the characteristics listed in Table 5, a change in the composition of firms across industries also contributes to the explained portion of the fall in the TPR. In particular, the rise in firms in industries related to oil and gas, which increased from 5.3% of the sample in period 1 to 8.4% of the sample in period 3, accounts for nearly a four percentage point decrease in the TPR, as oil and gas firms are associated with both a lower TPR and FPR.

[19] For example, the predicted FPR in period 2 is $5.3\% - 1.5\% = 3.8\%$.

Based solely on changes in characteristics and the observed decline in the distress rate, our estimates imply that the violation rate would have declined from 8.9% in period 1 to 5.7% in period 2 and 3.8% in period 3. The 5.1 percentage point predicted drop in violations across the full period caused by changes in borrower and lender characteristics explains roughly two-thirds of the overall fall in the violation rate. The remainder is attributable to the Unexplained Portion of the fall in the FPR and TPR.

5.4 The Impact of Unexplained Changes

Although changes in the rate of distress and characteristics can explain the bulk of the fall in violations, we are unable to explain the remaining one-third of the decline. One possibility is that we fail to account for other changes in the composition of borrowers, lenders, or loans that could help close the gap. Alternatively, the unexplained portion of the trend could reflect temporal changes in loan party preferences or covenant technology that are independent of the composition of the sample.

To shed more light on the magnitude of the unexplained changes in violations, we compute counterfactual values of the FPR, TPR, and violation rate, as well associated estimates of our model parameters, using the unexplained portions of the FPR and TPR from Table 5. In the first two columns of Table 7, we compute the FPR and TPR as the actual values in period 1 plus the unexplained portion of the change reported in Table 5,[20] which can be interpreted as the evolution of the FPR and TPR absent any changes in the specified sample characteristics. As in Table 6, we compute the predicted violation rate using equation (2) and the counterfactual values of the FPR and TPR from the first two columns, combined with the realized default rate.

The first two columns of Table 7 show that that the unexplained FPR and TPR decline over

[20] For example, the predicted FPR in period 2 is $5.3\% - 1.6\% = 3.7\%$.

the sample period in patterns that are more moderate than Table 2. The counterfactual FPR falls throughout the sample period, and the TPR rises slightly from period 1 to 2 and then drops in period 3. Meanwhile, the predicted violation rate drops from 8.9% to 4.0% rather than to the realized rate of 1.4% in Table 2.

The last three columns of Table 7 report counterfactual parameter estimates produced using the counterfactual TPR and FPR values and the procedure outlined in Section 4.2, which we illustrate in Figure 10. After accounting for changes in characteristics, the estimate of μ_D rises between the first and second periods but falls back by period 3, implying that all unexplained improvements in covenant technology that occurred during 2004-2011 disappeared in the 2012-2019 period. Due to the small sample of distressed firms during 2012-2019, the estimates are measured with substantial error, making inferences challenging. One potential driver behind this unexplained decline in covenant technology is that cash-flow based covenants have become less informative, as borrowers pushed to dilute EBITDA-based covenants through "add-backs" that disconnect the covenant definition from actual cash flow performance (see, e.g., Badawi, Dyreng, de Fontenay, and Hills, 2022).

The roughly 80% increase in the preference parameter estimated using unexplained changes in the TPR/FPR (shown in Table 7) is much less dramatic than the nearly 880% increase estimated using realized changes in the TPR/FPR (shown in Table 3). This comparison suggests that most of the estimated shift in preferences can be explained by a compositional shift in the public-corporation loan market toward large borrowers and transactional lenders that have a greater willingness to forego early detection of distress in exchange for fewer costly renegotiations. Nevertheless, the 80% unexplained increase in R implies a significantly greater willingness to miss distressed firms even holding constant the composition of borrowers and lenders. This change happens predominantly in the years following the GFC, when interest rates were low and other measures of financial market sentiment were high. This counterfactual outcome is evident in Figure 10, which shows that the unexplained fall in the FPR and TPR is consistent with a shift along a constant ROC curve.

6 Conclusions

We offer a conceptual lens to explore the fact that the incidence of financial covenant violations among U.S. public firms has fallen dramatically over the last two decades, coincident with a drop in the number and restrictiveness of financial covenants in corporate loan agreements. Our model proposes that covenants are set to trade off the costs of false negatives, which include lower recovery rates in the event of bankruptcy, with the costs of false positives, which include renegotiations costs and the potential for hold up. The model allows us to conduct two decompositions of the data to understand the causes and consequences of the trend.

First, we decompose the violation rate into the distress rate, the FPR, and the TPR and find that a modest fall in the distress rate explains 25% of the overall decline in violations and a sharp fall in the FPR explains roughly 61% of the trend. The reduction in false positives represents an improvement in outcomes, as borrowers and lenders more frequently avoid the costs of renegotiation for violations that would be resolved without a consequential change to the lending agreement. The TPR remains relatively constant until the GFC and falls modestly thereafter, explaining the remaining 14% of the overall decline in violations. Although the failure to catch distressed borrowers before bankruptcy leads to lower recovery rates, we estimate that the observed drop in the TPR would have a relatively minor impact on the financial sector even if the corporate distress rate returns to higher levels.

Second, we decompose the trends in the FPR and TPR into a portion that we can explain with observable changes in loan market characteristics and a residual unexplained portion. Our analysis shows that a small set of characteristics – borrower size, borrower credit rating, lender type, loan market segment, and the use of balance sheet covenants – can explain roughly 52% of the total fall in the FPR and 69% of the total fall in the TPR. Together with the fall in the distress rate, observable changes in the loan market explain more than two-thirds of the overall decline in violations.

Although most of the aggregate trend is a natural consequence of a compositional shift among public firms towards larger, rated borrowers that raise debt from transactional lenders, our findings hint that heightened investor sentiment has also influenced contractual restrictiveness. The unexplained drops in the FPR and TPR after 2012 indicate that lenders were willing to relinquish some of their monitoring ability during a period of low interest rates and generous credit supply. Nevertheless, the totality of our evidence alleviates concerns about excessively loose covenants by showing that the dramatic fall in violations is best attributed to a shift in the sample of public firms towards large borrowers and lenders with a greater willingness to forego early detection of distress in exchange for fewer costly renegotiations.

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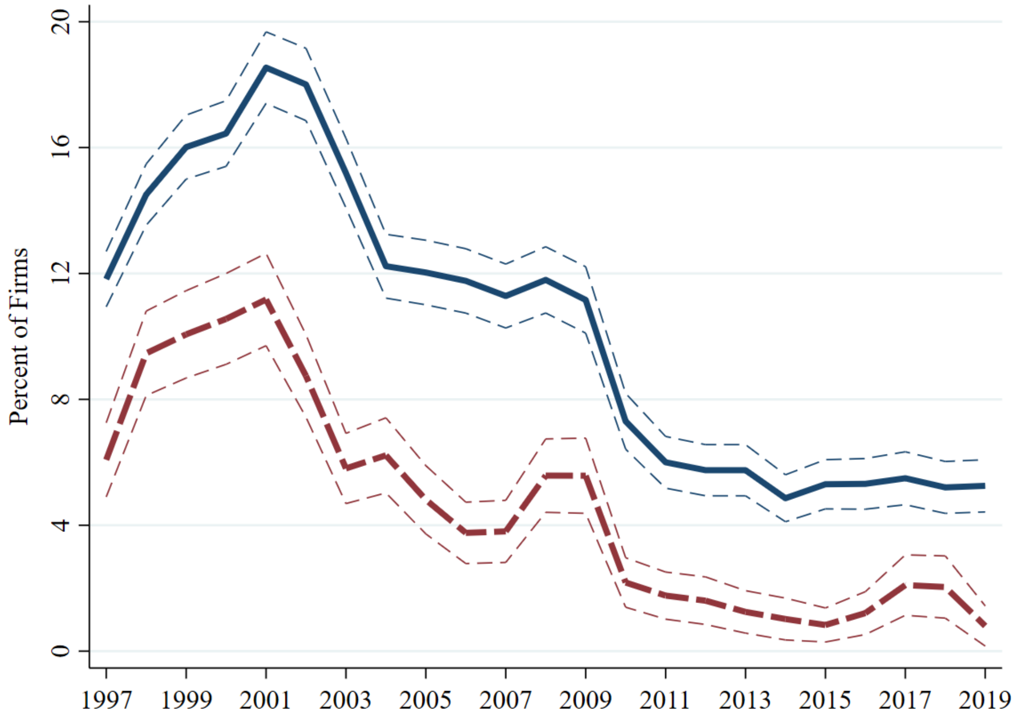
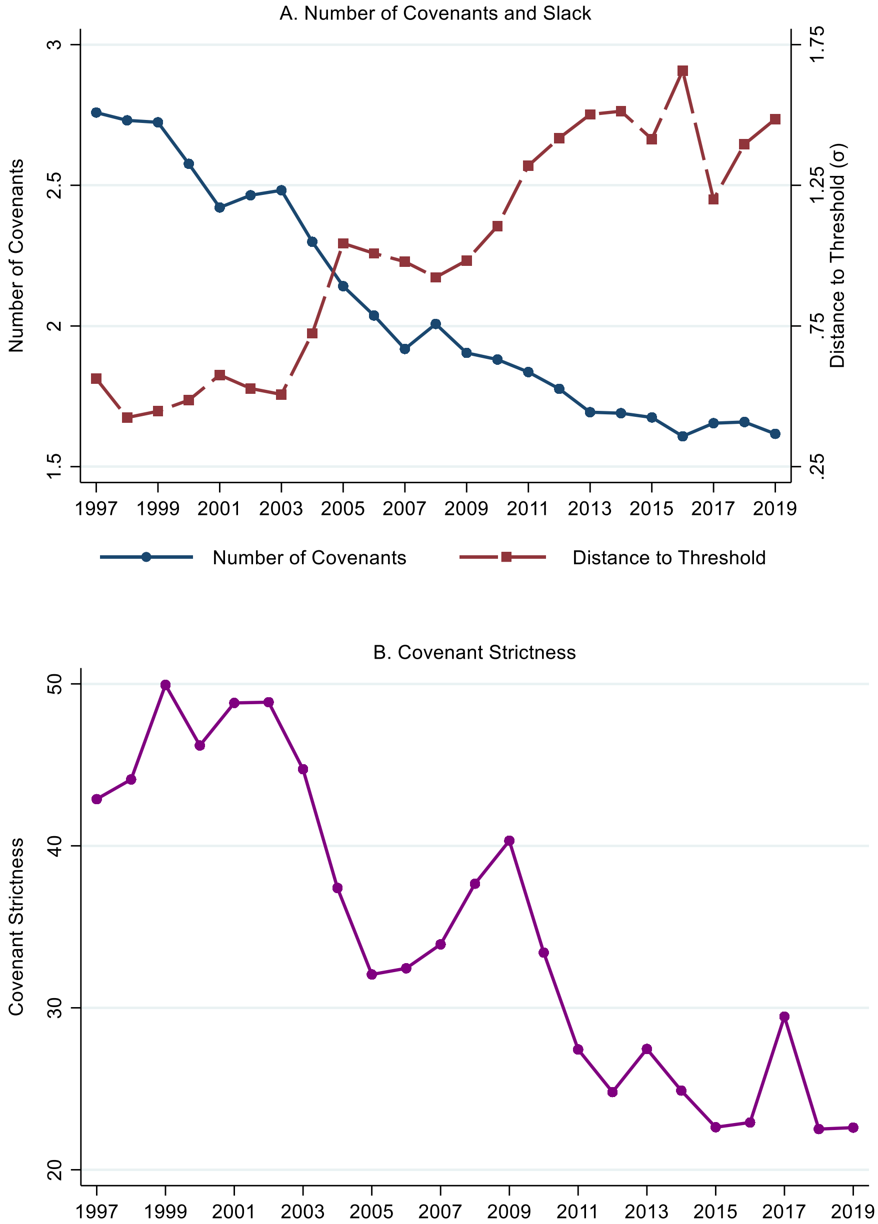
Figures and Tables

Figure 1. Reported Total and New Covenant Violations



Note: This figure plots the annual percent of firms that report a financial covenant violation in a 10-K or 10-Q filing between 1997 and 2019. The solid blue line displays the incidence of total violations and the long-dash red line depicts the incidence of new violations, defined as violations by firms that did not violate in the previous four quarters. Small-dash lines plot 95% confidence intervals for the annual proportions. The total violation sample consists of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have data available in Compustat. The new violation sample contains the subset of firm-year observations that have a loan outstanding with covenant and lender data available in Dealscan.

Figure 2. Covenants in Corporate Loan Agreements



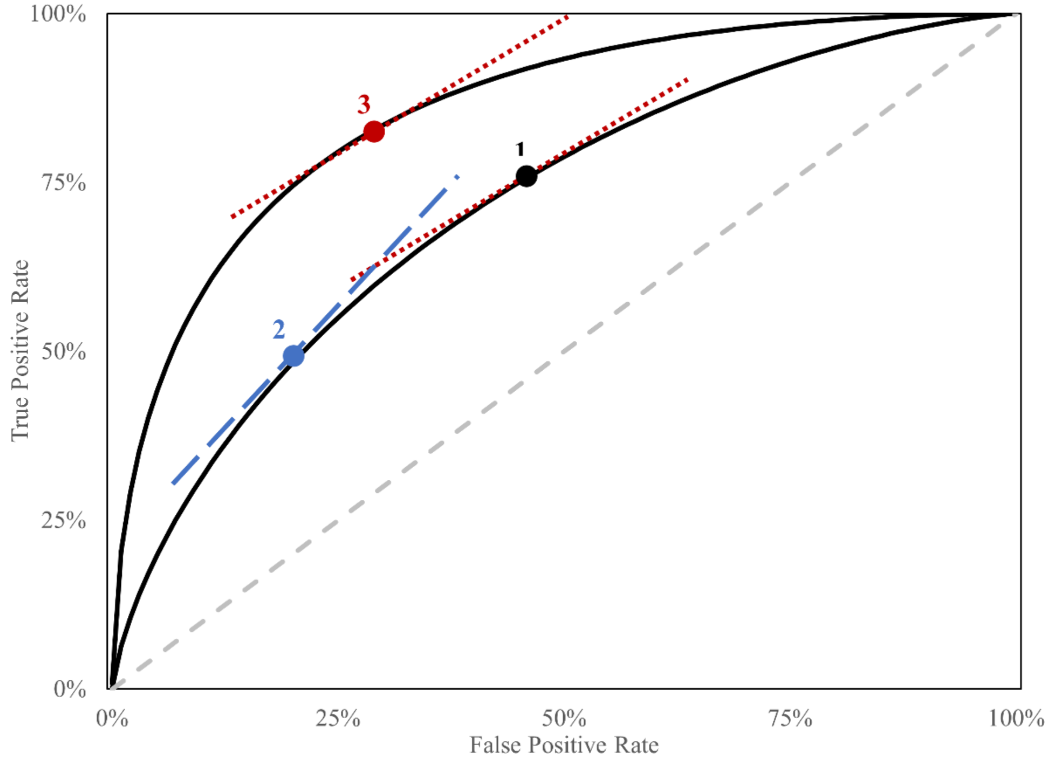
Note: This figure plots the annual average number of financial covenants in U.S. corporate loans, their slack, and their ex-ante strictness. The solid blue line in Panel A (left axis) depicts the annual average number of financial covenants in a loan package and the dashed red line in Panel A (right axis) displays the annual average covenant slack, measured as the distance in standard deviations between the contractual threshold and underlying financial metric for the tightest covenant at loan origination. The solid purple line in Panel B displays the average annual covenant strictness, using the Murfin (2012) measure. The loan sample consists of loan packages with covenant and lender data available in Dealscan issued to U.S. nonfinancial firms in Compustat between 1997 and 2019.

Figure 3. Financial Covenants as a Statistical Classification Tool

	Distressed (D = 1)	**Non-Distressed (D = 0)**
Violator (V = 1)	True Positive (2.5%)	False Positive (2.9%)
Non-Violator (V = 0)	False Negative (1.1%)	True Negative (93.6%)

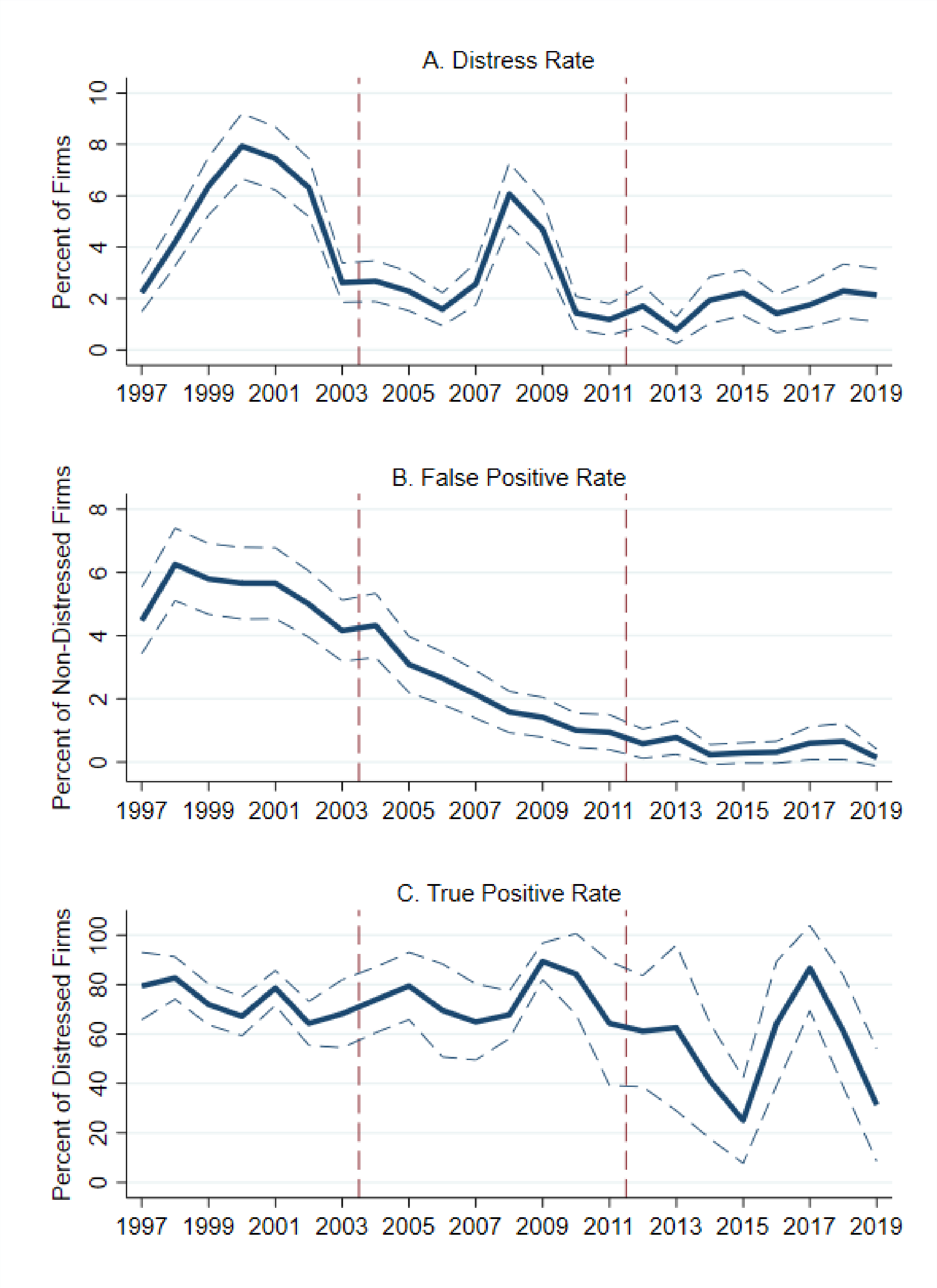
Note: This figure summarizes the role of financial covenants as a statistical classification tool. Cells report empirical frequencies based on the set of firm-years that we can determine violation outcomes. We classify a firm-year as distressed if the firm files for bankruptcy over the subsequent year or there is a consequential violation. We consider a violation to be consequential if it is resolved through an amendment that raises the interest rate, reduces the loan commitment, forces repayment, or forces an asset sale/capital raising. The sample consists of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan.

Figure 4. Example ROC Curves and Optimal Outcomes



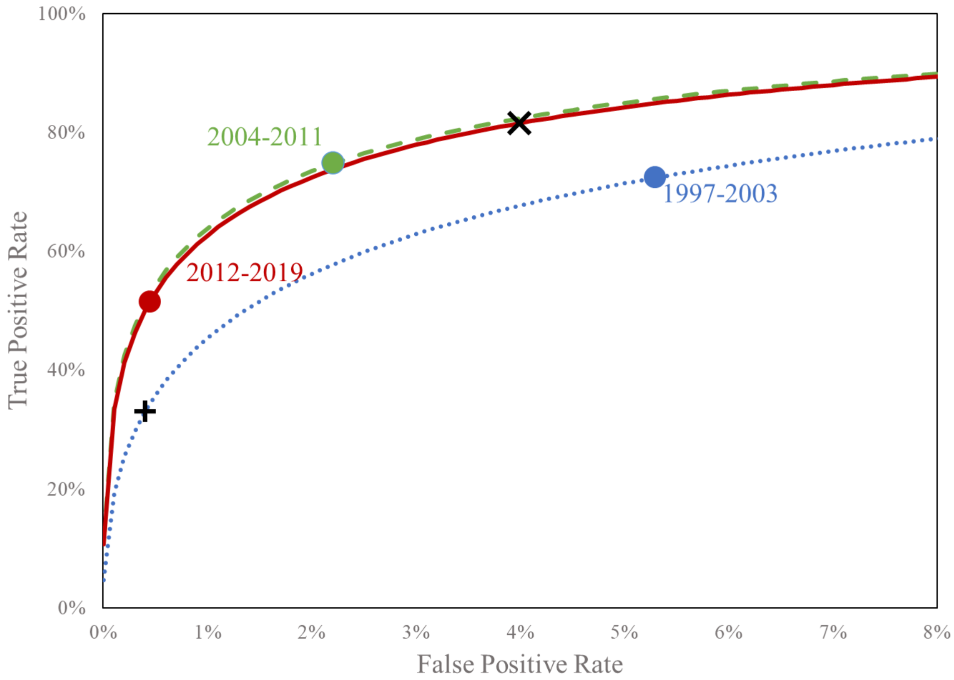
Note: This figure displays example ROC curves and optimal outcomes according to the model of financial covenant thresholds. Points 1, 2, and 3 represent the optimal FPR and TPR outcomes for different structural parameters. The 45-degree line represents an uninformative statistical test and the ROC curve furthest to the upper left represents better covenant technology. Points 1 and 3 are based on the same ratio of expected costs of a false positive to a false negative; Point 2 is based on a larger ratio.

Figure 5. Decomposing the Violation Rate



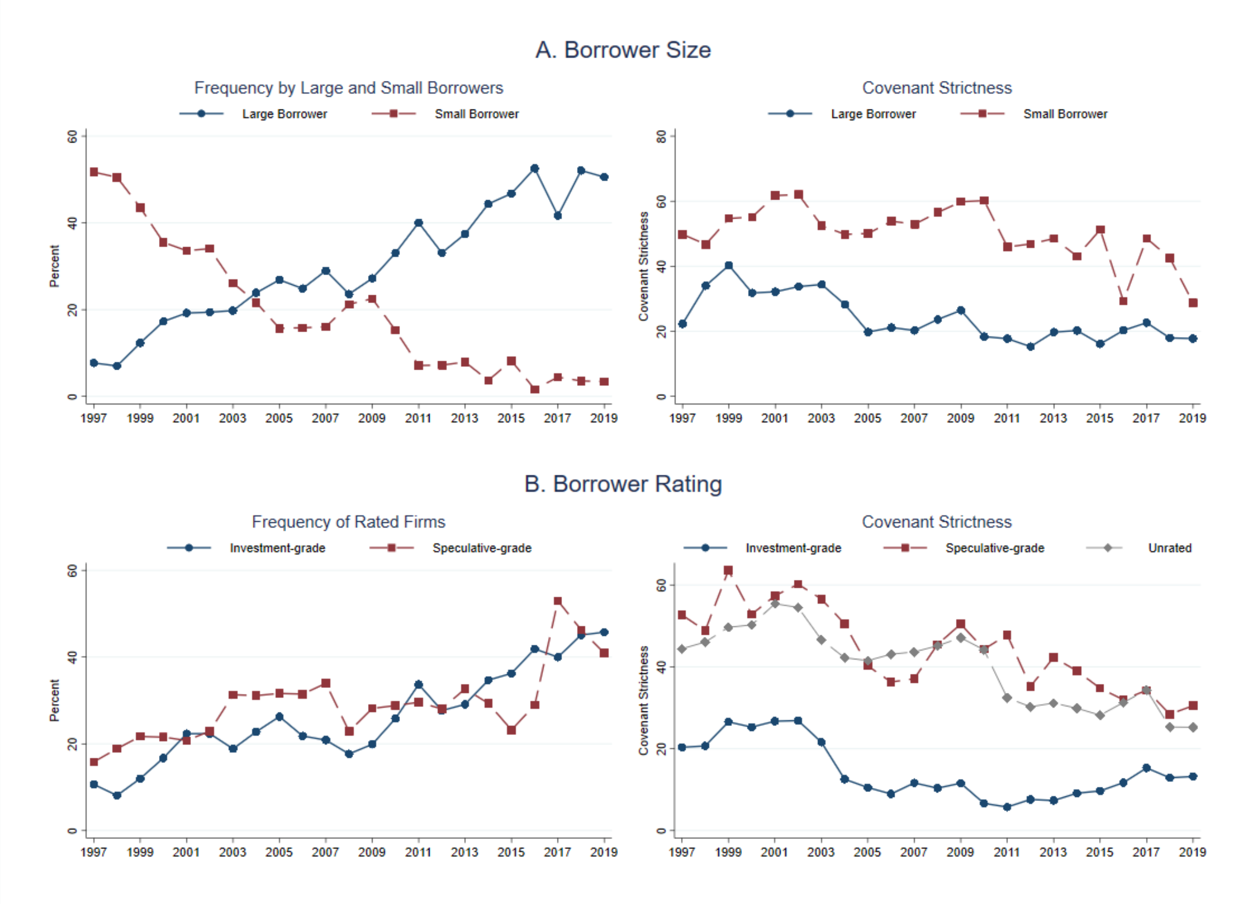
Note: This figure displays the annual percent of firms in distress (Distress Rate), the annual percent of non-distressed firms that report a covenant violation (False Positive Rate), and the annual percent of distressed firms that report a covenant violation (True Positive Rate). We classify a firm as distressed if it files for bankruptcy over the subsequent year or experiences a consequential violation. Dashed lines plot 95% confidence intervals for the annual proportions. Vertical lines divide the sample into three subperiods: 1997-2003, 2004-2011, and 2012-2019. The sample consists of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan.

Figure 6. Estimated ROC Curves



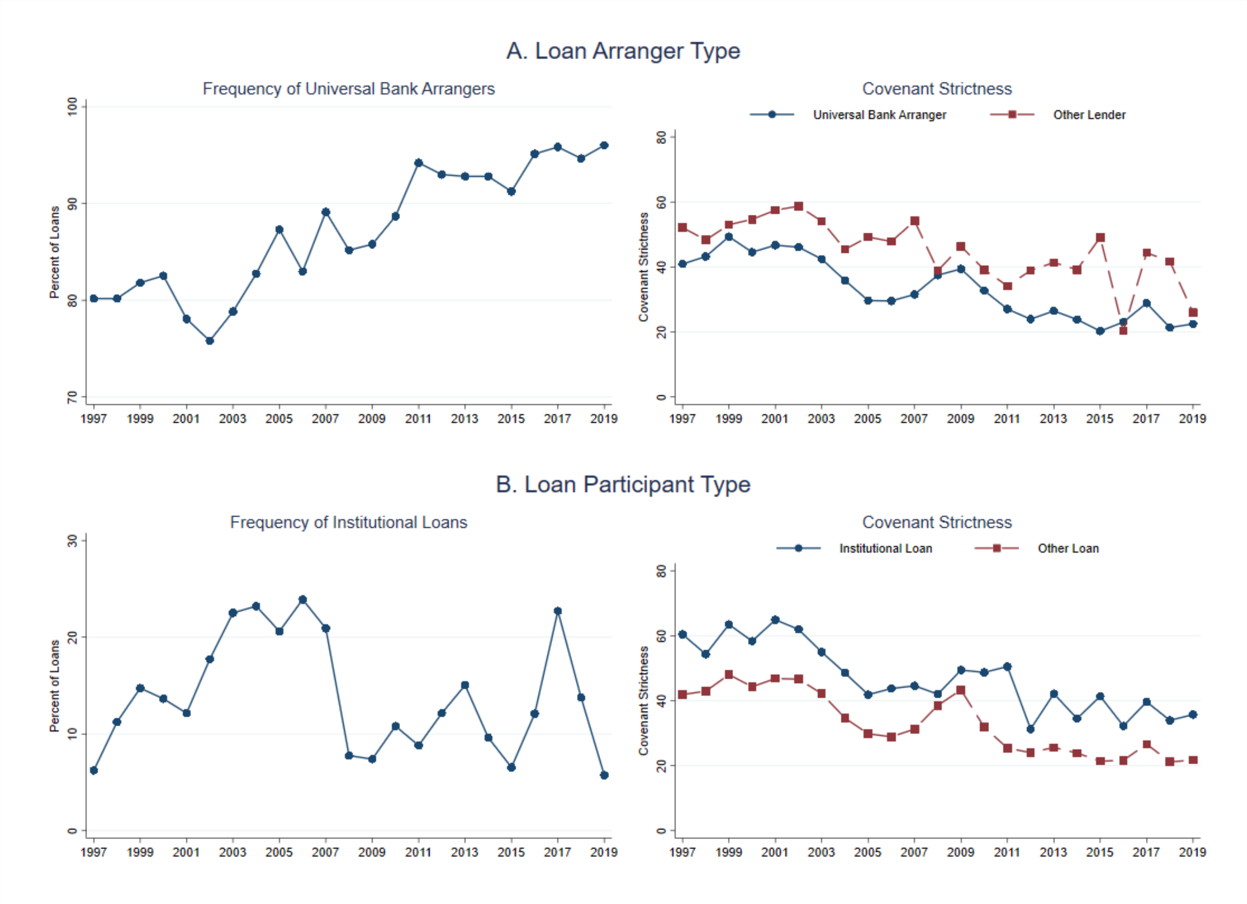
Note: This figure displays ROC curves estimated using our model and actual FPR, TPR outcomes realized in each period: 1997-2003 (blue dotted line), 2004-2011 (green dashed line), and 2012-2019 (red solid line). Large solid circles show the actual FPR, TPR outcome realized in each period. The black 'X' shows the counterfactual FPR, TPR outcome that would have prevailed in 2012-2019 if the estimated preference parameter remained at its 1997-2003 level. The black '+' shows the counterfactual FPR, TPR outcome that would have prevailed in 2012-2019 if the estimated covenant technology remained at its 1997-2003 level. The estimates are based on the sample of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan.

Figure 7. Borrower Composition and Covenant Strictness



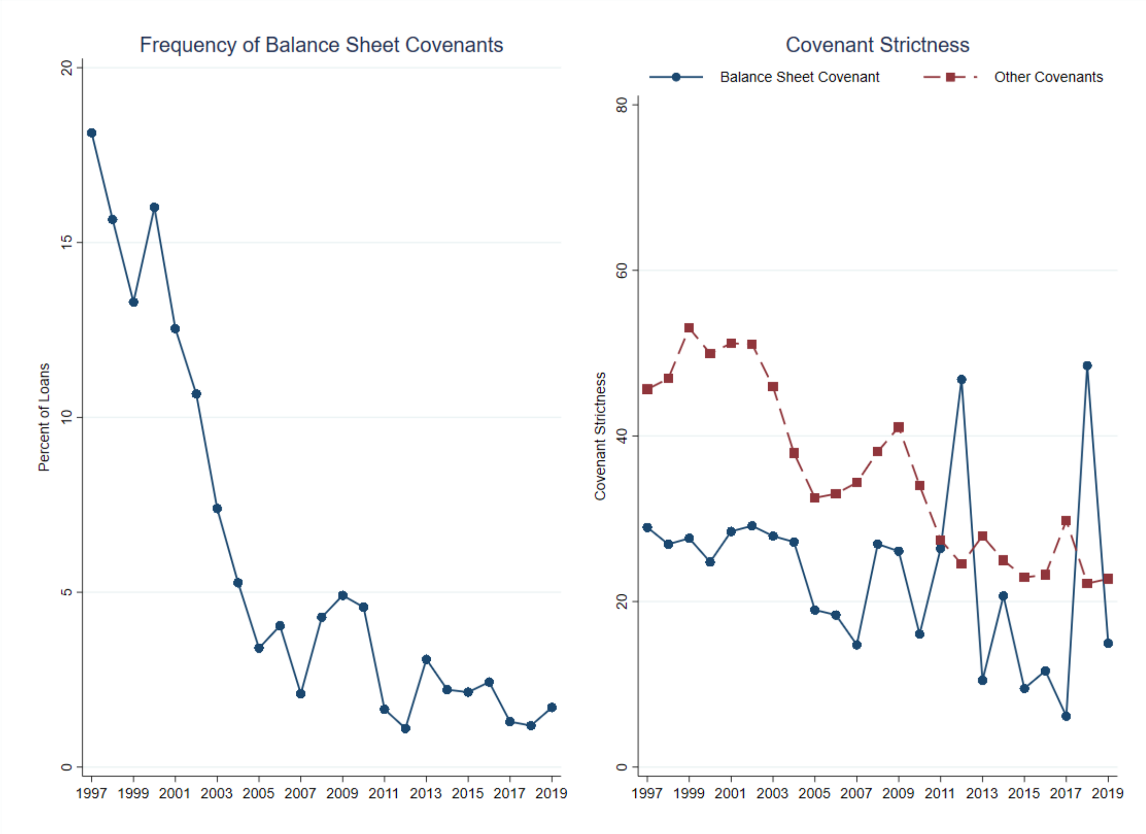
Note: This figure plots the change in borrower composition over time and the trend in covenant strictness across borrowers. Panel A compares borrowers with total assets in the top 25th (Large) or bottom 25th (Small) percentile of the empirical distribution using real 2000 dollars. Panel B compares unrated borrowers and borrowers that have an S&P long term issuer credit rating of investment-grade or speculative-grade. The sample includes packages with covenant and lender data available in Dealscan issued to U.S. nonfinancial firms in Compustat between 1997 and 2019.

Figure 8. Lender Composition and Covenant Strictness



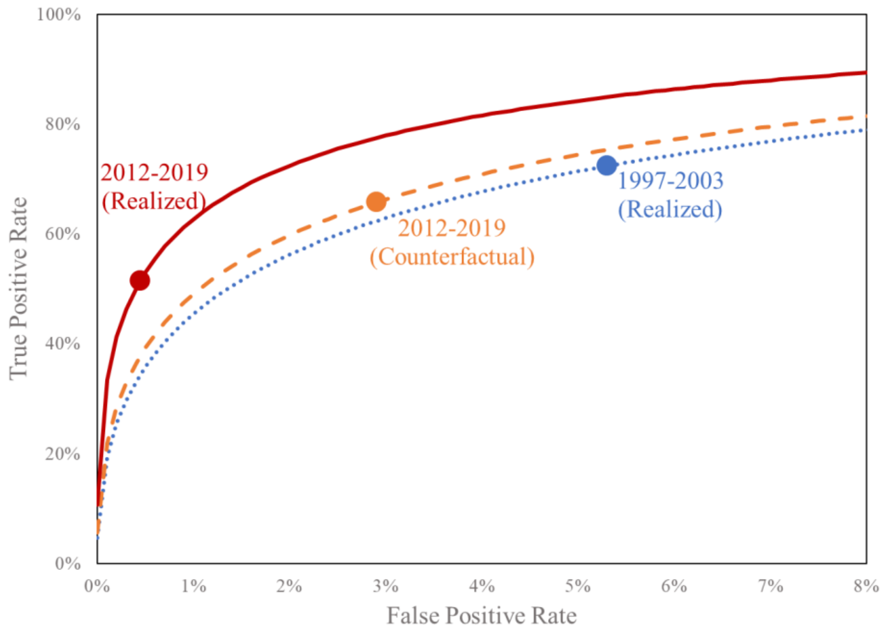
Note: This figure plots the change in lender composition over time and the trend in covenant strictness across lenders. Panel A compares packages with a lead lender that is a universal bank and all other packages. Panel B compares packages with an institutional loan with all other packages. The sample includes packages with covenant and lender data available in Dealscan issued to U.S. nonfinancial firms in Compustat between 1997-2019.

Figure 9. Covenant Type and Covenant Strictness



Note: This figure plots the change in the type of covenants over time and the trend in covenant strictness across covenant types. The figure compares packages with a balance sheet covenant with all other packages. The sample includes packages with covenant and lender data available in Dealscan issued to U.S. nonfinancial firms in Compustat between 1997 and 2019.

Figure 10. Counterfactual ROC Curve



Note: This figure displays FPR and TPR outcomes and the implied ROC curves using the model from Section 3. The blue dotted line and red solid line use actual FPR, TPR outcomes realized in 1997-2003 and 2012-2019, respectively. The orange dashed line plots the counterfactual ROC curve estimated using the Unexplained Portion of the FPR, TPR from the Blinder-Oaxaca decomposition presented in Table 5.

Table 1. No Violation and Creditor Recovery Rates

This table displays estimates from ordinary least squares regressions where the dependent variable is the percentage ultimate recovery rate determined by Moody's Analytics. "Firm Recovery Rate" is the dollar-weighted average of the recovery rates of the debt instruments in the pre-petition capital structure. "No Violation" is an indicator that equals one if the firm did not report a covenant violation in the year before bankruptcy. "Bank Debt Share" is the fraction of prepetition debt structure consisting of revolvers and term loans, according to Moody's. The sample consists of 403 corporate defaults that were resolved in bankruptcy, have recovery data available in Moody's Ultimate Recovery Database, and can be matched to our main firm-year violation sample. Borrower characteristics are from the quarter closest to the bankruptcy filing date and are winsorized at the 1/99% levels. Standard errors are reported in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Firm Recovery Rate			
	(1)	(2)	(3)	(4)
No Violation	-11.392***	-10.092***	-9.793***	-6.699**
	(2.805)	(2.977)	(3.172)	(3.188)
Operating Cash Flow / Assets			3.345	-0.656
			(17.672)	(17.269)
Debt / Assets			-6.615	-6.276
			(5.399)	(5.268)
Interest Expense / Assets			256.415*	278.084**
			(137.745)	(134.490)
Net Worth / Assets			11.124	10.203
			(8.447)	(8.244)
Current Ratio			1.353	1.334
			(2.027)	(1.978)
Market-to-Book Ratio			6.412	5.290
			(6.851)	(6.690)
Cash / Assets			-23.915	-14.175
			(18.617)	(18.322)
Bank Debt Share				0.187***
				(0.046)
Year Fixed Effects	No	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	Yes	Yes
Observations	403	402	365	365
Adjusted R-Squared	0.037	0.203	0.237	0.273

Table 2. Empirical Decomposition of the Violation Rate

This table presents an empirical decomposition of the violation rate for three subperiods: 1997-2003, 2004-2011, and 2012-2019. Panel A decomposes the violation rate in each period into the distress rate, false positive rate, and true positive rate based on Equation (2). Panel B decomposes the change in the violation rate across periods based on Equation (3). The sample consists of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan. Standard errors are reported in parentheses.

	Violation	Distress	FPR	TPR
A. Decomposing the Violation Rate				
1. 1997-2003	8.9%	5.4%	5.3%	72.3%
	(0.3%)	(0.2%)	(0.2%)	(1.8%)
2. 2004-2011	4.3%	2.9%	2.2%	74.8%
	(0.2%)	(0.2%)	(0.1%)	(2.4%)
3. 2012-2019	1.4%	1.8%	0.5%	51.5%
	(0.1%)	(0.2%)	(0.1%)	(4.4%)
B. Decomposing the Change in the Violation Rate				
Period 1 to 2	-4.6%	-1.8%	-2.9%	0.1%
Period 2 to 3	-2.9%	-0.6%	-1.7%	-0.7%
Period 1 to 3	-7.6%	-1.9%	-4.6%	-1.1%

Table 3. Parameter Estimates and Counterfactual Outcomes

Panel A presents parameter estimates for the model in Section 3. μ_D represents the difference in means of the distributions generating the signals used in financial covenants, between distressed and non-distressed firms. R is the ratio of expected costs of false positives to false negatives $\frac{(1-\rho)}{\rho}\frac{C_{FP}}{C_{FN}}$. t^* is the optimal covenant threshold. Standard errors are reported in parentheses. Panel B presents two sets of counterfactual analysis. In the columns under "Hold Preferences Fixed," R is held at its estimated 1997-2003 level and the technology parameter μ_D varies according to the estimates in Panel A. In the columns under "Hold Technology Fixed," μ_D is held at its estimated 1997-2003 level and the preference parameter R varies according to the estimates in Panel A. The implied FPR and TPR are estimated using the model in Section 3, and the violation rate is computed using the realized distress rate in Table 2 and the implied FPR, TPR. The estimates are based on the sample of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan.

	A. Parameter Estimates			B. Counterfactual Outcomes					
				Hold Preferences Fixed			Hold Technology Fixed		
	μ_D	R	t^*	FPR	TPR	Violation	FPR	TPR	Violation
1997-2003	2.21	3.10	1.62	5.3%	72.3%	8.9%	5.3%	72.3%	8.9%
	(0.10)	(0.14)	(0.02)						
2004-2011	2.68	6.06	2.01	3.9%	82.1%	6.1%	2.7%	61.4%	4.4%
	(0.17)	(0.44)	(0.02)						
2012-2019	2.65	30.29	2.61	4.0%	81.5%	5.4%	0.4%	33.0%	1.0%
	(0.44)	(4.73)	(0.06)						

Table 4. Determinants of the FPR and TPR

Panel A reports estimated marginal effects from Probit regressions on borrower, lender, and loan characteristics, and Fama-French 12 industry indicators. The dependent variable is an indicator that equals one if the firm reports a violation during the year. The sample consists of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan. We split the sample such that the FPR (TPR) regressions use only non-distressed (distressed) firms and coefficients report estimated marginal effects on the likelihood of a false positive (true positive) violation. Estimated marginal effects are computed using the delta method and standard errors are reported in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Panel B reports sample means for each variable by subperiod.

	A. Estimated Marginal Effects		B. Period Means		
	FPR	TPR	1997-2003	2004-2011	2012-2019
Borrower Size	-0.013***	-0.047***	5.792	6.715	7.500
	(0.001)	(0.012)			
Speculative-grade Rating	-0.002	-0.126***	0.178	0.274	0.320
	(0.003)	(0.034)			
Investment-grade Rating	-0.009*	0.110	0.133	0.198	0.286
	(0.005)	(0.086)			
Universal Bank	-0.006***	0.051	0.790	0.841	0.923
	(0.002)	(0.033)			
Institutional Loan	0.003	0.039	0.104	0.151	0.109
	(0.003)	(0.036)			
Balance Sheet Covenant	0.005*	-0.130**	0.139	0.049	0.024
	(0.003)	(0.051)			
Observations	29,719	1,102	12,040	11,351	7,430

Table 5. Blinder-Oaxaca Decomposition of the FPR and TPR

This table reports a Blinder-Oaxaca decomposition of the change in the FPR and TPR across three subperiods: 1997-2003 (Period 1), 2004-2011 (Period 2), and 2012-2019 (Period 3). Columns display estimates of the total change in the FPR and TPR across periods, the portion of the change explained by observable characteristics, the residual unexplained portion of the change, and the contribution of each observable to the total change. The decomposition is based on probit regression coefficients and sample means reported in Table 4. The sample consists of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan. Standard errors are reported in parentheses. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	False Positive Rate		True Positive Rate	
	Period 1 to Period 2	Period 1 to Period 3	Period 1 to Period 2	Period 1 to Period 3
Total Change	-0.031***	-0.048***	0.021	-0.242***
	(0.003)	(0.002)	(0.030)	(0.048)
Explained Portion	-0.015***	-0.025***	-0.030***	-0.143***
	(0.001)	(0.001)	(0.011)	(0.026)
Unexplained Portion	-0.016***	-0.024***	0.051*	-0.099**
	(0.002)	(0.002)	(0.027)	(0.040)
Borrower Size	-0.0135***	-0.0215***	-0.0249***	-0.0630***
	(0.0010)	(0.0015)	(0.0076)	(0.0169)
Speculative-grade Rating	-0.0002	-0.0003	-0.0174***	-0.0392***
	(0.0003)	(0.0005)	(0.0063)	(0.0127)
Investment-grade Rating	-0.0006*	-0.0011*	-0.0000	-0.0007
	(0.0003)	(0.0006)	(0.0014)	(0.0020)
Universal Bank	-0.0004***	-0.0009***	-0.0005	0.0032
	(0.0001)	(0.0003)	(0.0016)	(0.0030)
Institutional Loan	0.0002	0.0000	0.0036	-0.0007
	(0.0002)	(0.0000)	(0.0036)	(0.0017)
Balance Sheet Covenant	-0.0005	-0.0006	0.0120**	0.0160**
	(0.0003)	(0.0004)	(0.0051)	(0.0064)
Observations	22,419	18,295	968	763

Table 6. Trend Due to Changes in Observable Characteristics

This table presents the predicted FPR, TPR, and violation rate that would have prevailed due to the evolution of observable characteristics. The 1997-2003 FPR, TPR, and violation rate are the actual values in Period 1. The 2004-2011 FPR (TPR) is estimated using the Period 1 level plus the Explained Portion of the change in the FPR (TPR) from Period 1 to Period 2 from Table 5. The 2004-2011 violation rate is estimated using the implied FPR and TPR and the realized distress rate in Table 2. The 2012-2019 FPR, TPR, and violation rate are constructed analogously. Standard errors are reported in parentheses.

	FPR	TPR	Violation
1997-2003	5.3%	72.3%	8.9%
	(0.2%)	(1.7%)	(0.3%)
2004-2011	3.8%	69.4%	5.7%
	(0.1%)	(2.7%)	(0.2%)
2012-2019	2.8%	58.0%	3.8%
	(0.1%)	(5.1%)	(0.2%)

Table 7. Implications of Unexplained Changes

This table presents estimates of the counterfactual FPR, TPR, violation rate and structural parameters that would have prevailed absent the changes in observable characteristics. The 1997-2003 FPR and TPR are the actual values from Period 1. The 2004-2011 FPR (TPR) is estimated using the Period 1 level plus the Unexplained Portion of the change in the FPR (TPR) from Period 1 to Period 2 from Table 5. The 2004-2011 violation rate is estimated using the implied FPR and TPR and the realized distress rate in Table 2. The 2012-2019 FPR, TPR, and violation rate are constructed analogously. The structural parameter estimates are based on the model in Section 3 and the implied FPR, TPR values. Standard errors are reported in parentheses.

	FPR	TPR	Violation	μ_D	R	t^*
1997-2003	5.3%	72.3%	8.9%	2.21	3.10	1.62
	(0.2%)	(1.8%)	(0.3%)	(0.10)	(0.14)	(0.02)
2004-2011	3.7%	77.7%	5.8%	2.54	3.73	1.79
	(0.1%)	(2.7%)	(0.2%)	(0.12)	(0.14)	(0.01)
2012-2019	2.9%	62.5%	4.0%	2.21	5.69	1.89
	(0.2%)	(3.8%)	(0.1%)	(0.92)	(1.59)	(0.12)

Appendix 1. Measurement of Covenant Violations

This appendix assesses the robustness of the trend in financial covenant violations.

Table A.1.A reports the violation rate based on three alternative measures. The first two columns report the violation rate and number of observations in our main firm-year violation sample, which we base on Nini, Sufi, and Smith (2012) and extend through 2019. RS (2009) columns use violations collected by Roberts and Sufi (2009) and available on Roberts' website. CR (2008) columns use violations imputed from covenant thresholds in Dealscan and realized accounting values in Compustat, as in Chava and Roberts (2008). The sample consists of firm-years from U.S. nonfinancial firms that can be matched to EDGAR and have data available in Compustat.

Figure A.1.A plots the distribution of distance-to-violation for the tightest covenant in each firm-quarter. The sample consists of firm-quarter observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan, excluding quarters with a loan origination and loans with negative slack at origination.

Figure A.1.B plots the annual number of amendments to packages in our loan sample that are recorded in Dealscan. We collect amendments from Dealscan's "dealamendment" file. Our loan sample consists of packages with covenant and lender data available in Dealscan issued to U.S. nonfinancial firms in Compustat between 1997 and 2019.

Table A.1.A. Alternative Violation Measurement

	Reported Violations Used in Analysis		Reported Violations RS (2009)		Imputed Violations CR (2008)	
Year	**Viol Rate**	**Obs**	**Viol Rate**	**Obs**	**Viol Rate**	**Obs**
1997	11.82	5,177	5.41	5,177	10.71	1,896
1998	14.51	5,032	6.66	5,032	13.98	2,053
1999	16.02	4,989	6.92	4,989	14.35	2,070
2000	16.45	4,858	7.04	4,858	12.51	2,014
2001	18.54	4,487	7.89	4,487	13.33	1,898
2002	18.01	4,293	6.36	4,293	12.41	1,909
2003	15.19	4,055	5.62	4,055	10.93	1,811
2004	12.23	4,014	4.01	4,014	6.54	1,728
2005	12.03	3,865	4.01	3,865	4.70	1,616
2006	11.76	3,808	3.47	3,808	3.32	1,566
2007	11.28	3,722	3.84	3,722	4.37	1,488
2008	11.80	3,611	3.93	3,611	5.98	1,471
2009	11.16	3,423	3.45	3,423	5.18	1,409
2010	7.30	3,313	1.75	3,313	4.45	1,349
2011	6.00	3,216	1.06	3,216	4.14	1,231
2012	5.75	3,148	.	0	2.94	1,121
2013	5.75	3,148	.	0	2.00	1,051
2014	4.86	3,190	.	0	3.02	1,028
2015	5.30	3,149	.	0	1.63	1,043
2016	5.32	2,991	.	0	1.54	975
2017	5.49	2,821	.	0	2.09	861
2018	5.20	2,787	.	0	2.55	785
2019	5.25	2,779	.	0	1.47	747

Figure A.1.A. Financial Ratio Manipulation

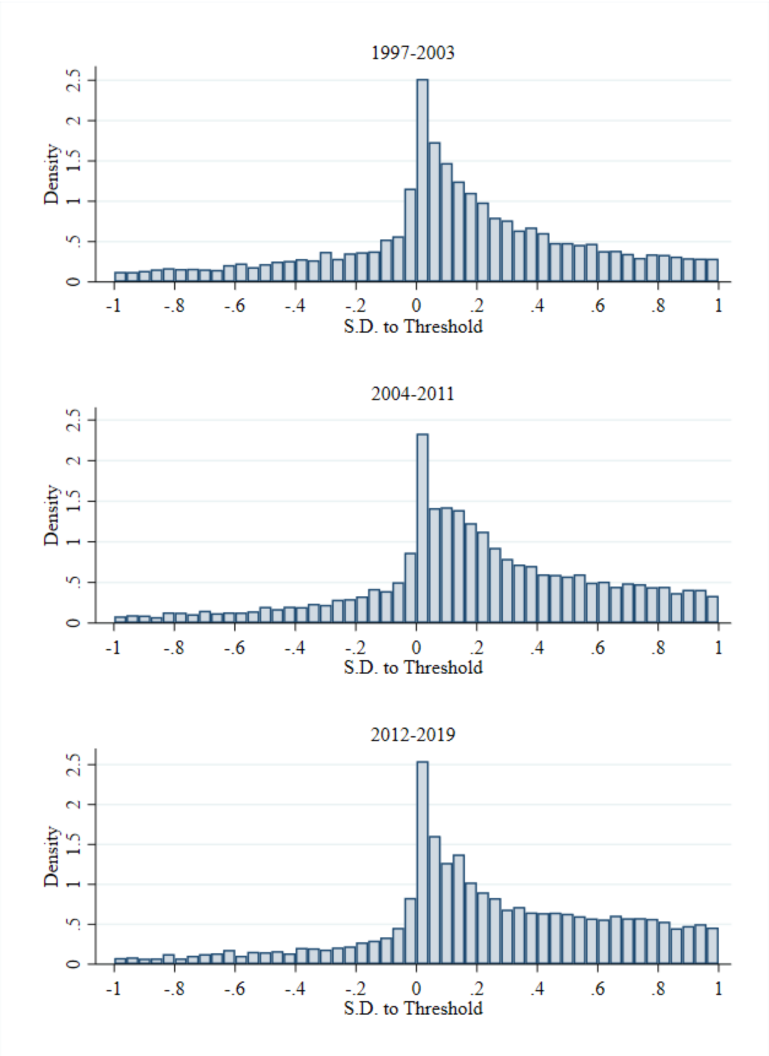
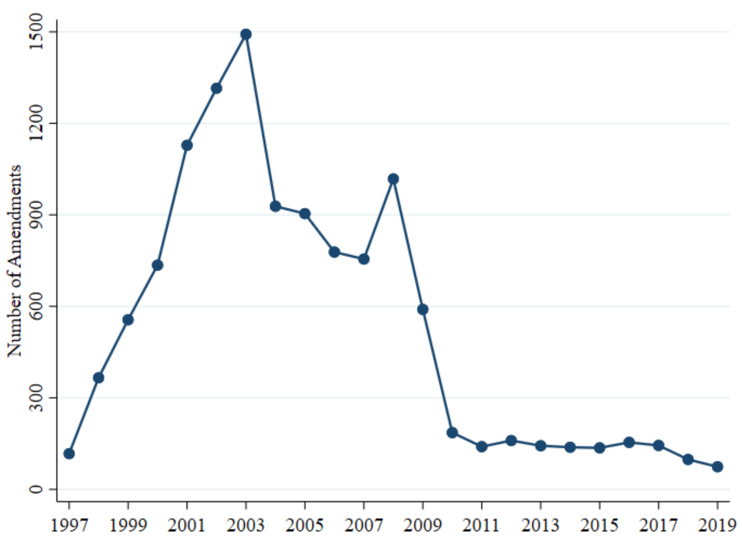


Figure A.1.B. Loan Amendments in Dealscan



Internet Appendix for

Losing Control?
The Two-Decade Decline in Loan Covenant Violations

September 2023

Internet Appendix. Measurement of Distress

This appendix assesses the robustness of the decomposition of the trend and structural estimation to alternative distress measures.

Figure IA.1 plots the annual percent of non-violating firms in distress based on four measures: i.) a bankruptcy filing within one year (as in the main analysis); ii.) Merton probability of default in the top 5th percentile of the distribution estimated following Bharath and Shumway (2008); iii.) a going concern warning; iv.) a bankruptcy filing within five years. Figures IA.2, IA.3, and IA.4 plot empirical decompositions of the violation rate (as in Figure 5 of the main analysis) using these alternative measures of distress for non-violating firms. Tables IA.1, IA.2, and IA.3 report an empirical decomposition of the violation rate into the distress rate, false positive rate, and true positive rate for three subperiods, 1997-2003, 2004-2011, and 2012-2019, and decomposes the change in the violation rate across periods (as in Table 2 of the main analysis) using these alternative measures of distress for non-violating firms. Tables IA.4, IA.5, and IA.6. present parameter estimates and counterfactual outcomes rate (as in Table 3 of the main analysis) using these alternative measures of distress for non-violating firms. Standard errors are reported in parentheses.

The sample used to construct this appendix is the same data used in corresponding analyses in the main text. The sample consists of firm-year observations from U.S. nonfinancial firms that can be matched to EDGAR and have a loan outstanding with covenant and lender data available in Dealscan. Going concern warnings are only available from Audit Analytics starting in 2000.

Figure IA.1. Alternative Measures of Distress for Non-Violating Firms

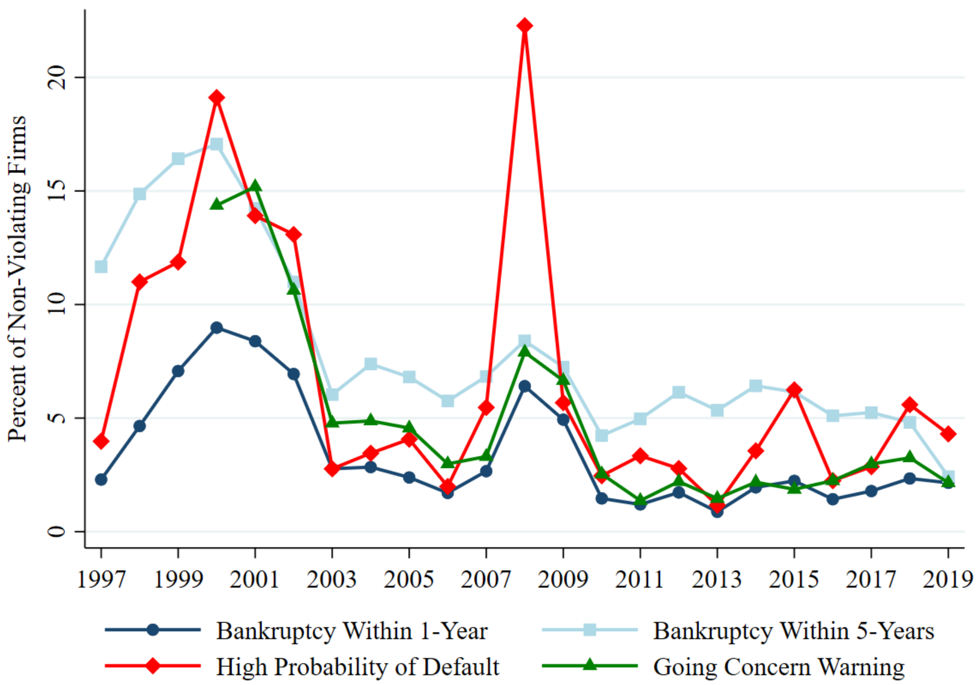


Figure IA.2. Decomposing the Violation Rate: Distress Measured Using High Probability of Default

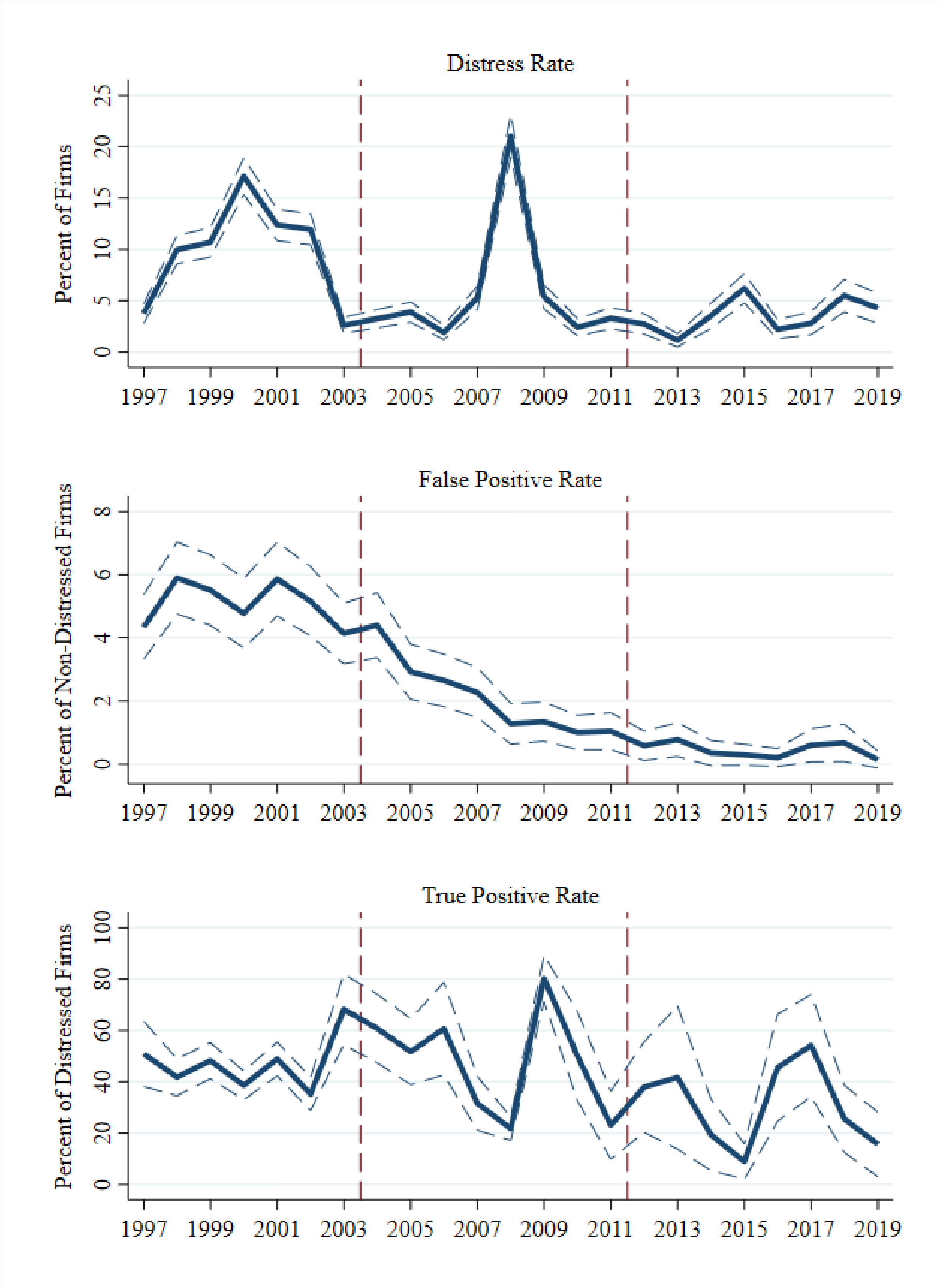


Figure IA.3. Decomposing the Violation Rate: Distress Measured Using Going Concern Warning

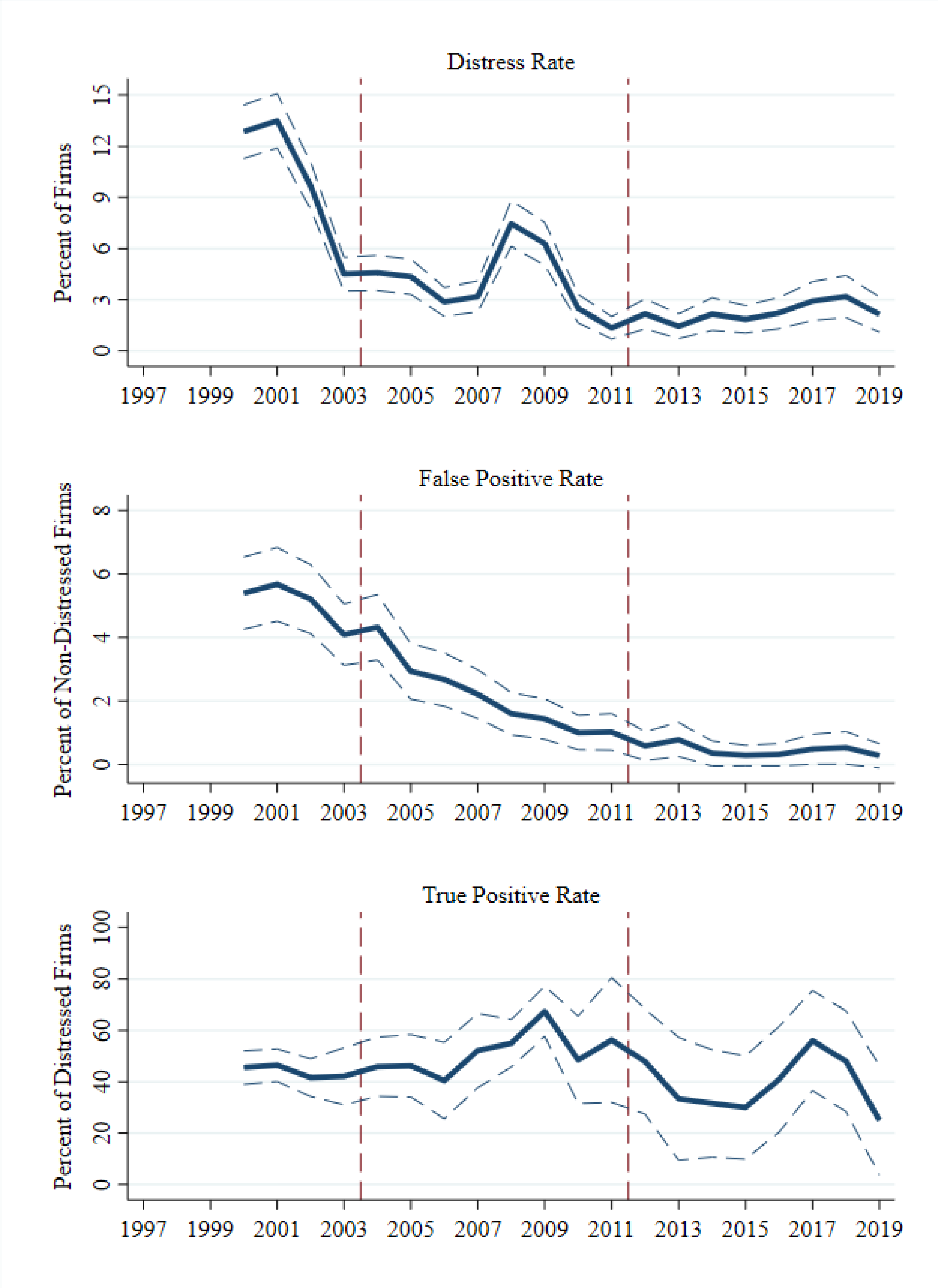


Figure IA.4. Decomposing the Violation Rate: Distress Measured Using Realized Bankruptcy Within 5 Years

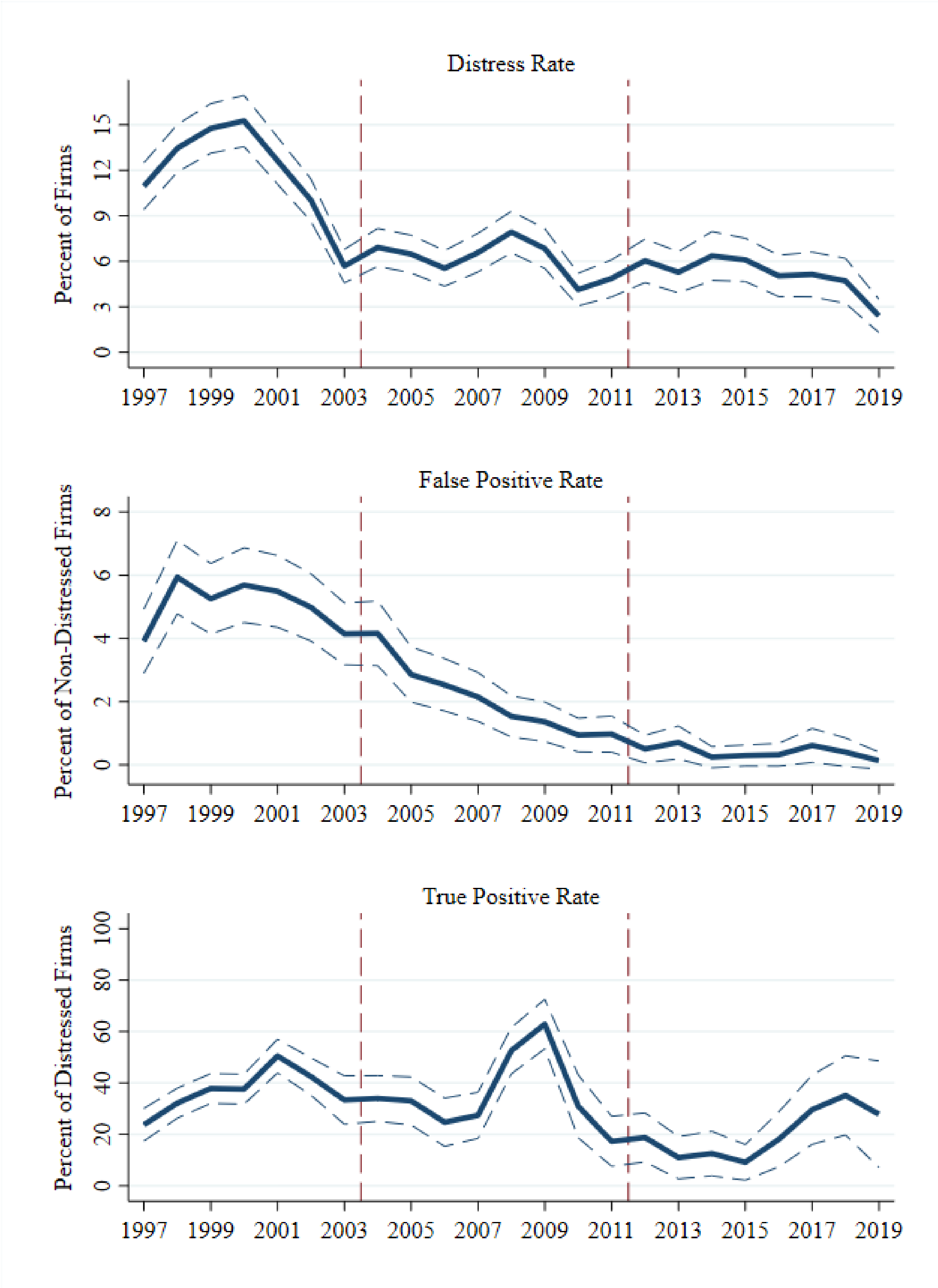


Table IA.1. Empirical Decomposition: Distress Measured Using High Probability of Default

	Violation	Distress	FPR	TPR
Decomposing the Violation Rate				
1. 1997-2003	8.9%	9.9%	5.1%	43.5%
	(0.3%)	(0.3%)	(0.2%)	(1.4%)
2. 2004-2011	4.3%	5.9%	2.2%	38.3%
	(0.2%)	(0.2%)	(0.1%)	(1.9%)
3. 2012-2019	1.4%	3.5%	0.5%	26.0%
	(0.1%)	(0.2%)	(0.1%)	(2.7%)
Decomposing the Change in the Violation Rate				
Period 1 to 2	-4.6%	-1.5%	-2.6%	-0.5%
Period 2 to 3	-2.9%	-0.6%	-1.6%	-0.7%
Period 1 to 3	-7.6%	-1.6%	-4.2%	-1.7%

Table IA.2. Empirical Decomposition: Distress Measured Using Going Concern Warning

	Violation	Distress	FPR	TPR
Decomposing the Violation Rate				
1. 1997-2003	5.2%	5.8%	5.1%	44.6%
	(0.2%)	(0.2%)	(0.3%)	(1.9%)
2. 2004-2011	4.3%	4.1%	2.2%	53.3%
	(0.2%)	(0.2%)	(0.1%)	(2.3%)
3. 2012-2019	1.4%	2.2%	0.5%	41.4%
	(0.1%)	(0.2%)	(0.1%)	(3.9%)
Decomposing the Change in the Violation Rate				
Period 1 to 2	-0.9%	-0.9%	-2.7%	0.5%
Period 2 to 3	-2.9%	-0.8%	-1.7%	-0.5%
Period 1 to 3	-3.9%	-1.5%	-4.4%	-0.2%

Table IA.3. Empirical Decomposition: Distress Measured Using Realized Bankruptcy Within 5 Years

	Violation	Distress	FPR	TPR
Decomposing the Violation Rate				
1. 1997-2003	8.9%	11.9%	5.1%	37.4%
	(0.3%)	(0.3%)	(0.2%)	(1.3%)
2. 2004-2011	4.3%	6.2%	2.1%	37.3%
	(0.2%)	(0.2%)	(0.1%)	(1.8%)
3. 2012-2019	1.4%	5.2%	0.4%	18.5%
	(0.1%)	(0.3%)	(0.1%)	(2.0%)
Decomposing the Change in the Violation Rate				
Period 1 to 2	-4.6%	-2.0%	-2.6%	0.0%
Period 2 to 3	-2.9%	-0.2%	-1.6%	-1.2%
Period 1 to 3	-7.6%	-1.2%	-4.1%	-2.3%

Table IA.4. Parameter Estimates and Counterfactual Outcomes: Distress Measured Using High Probability of Default

	Parameter Estimates			Counterfactual Outcomes					
				Hold Preferences Fixed			Hold Technology Fixed		
	μ_D	R	t^*	FPR	TPR	Violation	FPR	TPR	Violation
1997-2003	1.47	3.76	1.64	5.1%	43.5%	8.9%	5.1%	43.5%	8.9%
	(0.07)	(0.11)	(0.02)						
2004-2011	1.71	7.26	2.01	5.2%	53.2%	8.0%	1.9%	27.1%	3.4%
	(0.12)	(0.33)	(0.03)						
2012-2019	1.95	24.05	2.60	4.9%	61.8%	6.9%	0.2%	7.7%	0.5%
	(0.32)	(2.90)	(0.06)						

Table IA.5. Parameter Estimates and Counterfactual Outcomes: Distress Measured Using Going Concern Warning

	Parameter Estimates			Counterfactual Outcomes					
				Hold Preferences Fixed			Hold Technology Fixed		
	μ_D	R	t^*	FPR	TPR	Violation	FPR	TPR	Violation
1997-2003	1.50	3.78	1.64	5.1%	44.5%	7.4%	5.1%	44.5%	7.4%
	(0.09)	(0.11)	(0.03)						
2004-2011	2.08	7.55	2.01	4.6%	65.6%	7.2%	1.8%	27.5%	2.9%
	(0.14)	(0.41)	(0.03)						
2012-2019	2.37	29.46	2.61	4.0%	73.5%	5.6%	0.1%	6.6%	0.3%
	(0.41)	(4.14)	(0.06)						

Table IA.6. Parameter Estimates and Counterfactual Outcomes: Distress Measured Using Realized Bankruptcy Within 5 Years

	Parameter Estimates			Counterfactual Outcomes					
				Hold Preferences Fixed			Hold Technology Fixed		
	μ_D	R	t^*	FPR	TPR	Violation	FPR	TPR	Violation
1997-2003	1.32	3.63	1.64	5.1%	37.4%	8.9%	5.1%	37.4%	8.9%
	(0.06)	(0.09)	(0.02)						
2004-2011	1.71	7.44	2.03	5.4%	53.9%	8.4%	1.4%	19.3%	2.6%
	(0.12)	(0.34)	(0.03)						
2012-2019	1.74	21.82	2.64	5.4%	55.0%	8.0%	0.1%	4.6%	0.4%
	(0.28)	(2.63)	(0.06)						