The Value of Lending Relationships*

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Abstract

Lending relationships are prevalent in credit markets and are a potentially important driver of bank value, but little is known about the quantitative significance of this source of intangible capital. To estimate the value of these relationships, we develop a model of the lender's decision to enforce a contractual breach of pre-determined covenant thresholds based on the tradeoff between the cost of potential relationship termination and the benefits of increased fees and reduced risk. We find that the implied value of a relationship to the lender is 11.6% of loan principal, on average, and is significantly higher for more opaque borrowers with fewer outside options. At the bank level, relationship capital is estimated to be 6.6% of total assets or 41.2% of total capital (i.e. equity capital plus relationship capital), with significant heterogeneity across banks and over time. Nearly a quarter of aggregate relationship capital was lost in the Great Recession; in contrast with equity capital, relationship capital has not recovered. Finally, we show that banks' market-to-book ratios are positively associated with relationship capital, consistent with the market recognizing the value of the underlying relationships.

JEL Classification: G21, G32, K12, L14, E32, E44

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1 Introduction

Outside of the financial sector, the intensity of intangible capital increased by over 60% between 1975 and 2016, and among its components, customer capital, the capitalized value of customer relationships, consistently comprises a majority (Gourio and Rudanko 2014; Ewens, Peters, and Wang 2019).[1] Less is known about the value of intangible capital in the financial sector, despite the anecdotal and empirical relevance of relationships between lenders and borrowers (see, for example, Boot 2000 for a survey). Relationship lending may benefit banks through retaining credible borrowers (Bharath, Dahiya, Saunders, and Srinivasan 2007) and tying related services to primary lending (Drucker and Puri 2005; Yasuda 2005; Ljungqvist, Marston, and Wilhelm 2006). Moreover, banks appear to vary in the extent to which they engage in relationship-oriented versus transactional lending (Bolton, Freixas, Gambacorta, and Mistrulli 2016), suggesting potential heterogeneity in the stock of relationship capital across banks. Yet, the quantitative importance of lending relationships to lenders remains an open question.

In this paper, we address this question by estimating, for the first time, the economic value of lending relationships to lenders. We introduce a revealed preference approach based on a decision frequently made by lenders that risks relationship termination: whether to enforce upon contractual breaches arising from financial covenants. We start with a simple theory in

[1] Several papers have made progress on the measurement and implications of intangible capital, typically in the non-financial sector: Bernstein and Nadiri 1989; Chan, Lakonishok, and Sougiannis 2001; Corrado, Hulten, and Sichel 2009; Eisfeldt and Papanikolaou 2013, 2014; Falato, Kadyrzhanova, and Sim 2013; Belo, Lin, and Vitorino 2014; Peters and Taylor 2017; Li, Qiu, and Shen 2018.

which a lender trades off the benefits and costs of enforcing a covenant breach. The two first order benefits of enforcement are fees for waiving the covenant breach and amending loan terms (Bird, Ertan, Karolyi, and Ruchti 2020b), and behavioral concessions that reduce default risk (Graham, Harvey, and Rajgopal 2005; Chava and Roberts 2008; Nini, Smith, and Sufi 2009, 2012; Roberts and Sufi 2009a; Falato and Liang 2016). The primary cost to the lender is lost relationship value due to the increased propensity of the borrower to terminate the relationship (Bird, Ertan, Karolyi, and Ruchti 2020b). This trade off implies a simple analytical formula for the value of relationships based on the three underlying primitives related to the marginal decision to enforce. Specifically, our model implies that the lender's willingness to risk terminating its relationship with the borrower depends on direct remuneration from waiver and amendment fees and reductions in borrower credit risk.

Estimating this tradeoff model requires that we observe the outcome of the lender's enforcement decision and quantify the first order elements of the lender's tradeoff, namely the length of lending relationships, the financial condition of borrowers over time, and waiver and amendment fees. We use bank-borrower matched data from Dealscan that we link to Compustat to identify lending relationships and borrower financials (e.g., Chava and Roberts 2008), and we collect data on waiver and amendment fees from borrower SEC Form 8-K filings. We measure the enforcement decision using Greg Nini's data on material covenant violations (Becher, Griffin, and Nini 2018).

Our empirical approach exploits threshold-based variation in the lender's ability to enforce a contractual breach that occurs around pre-set thresholds for individual financial covenants. We estimate the marginal enforcement rate for borrowers that just-breach their pre-set thresholds using a fuzzy regression discontinuity design, and then connect this marginal enforcement with variation in fees and borrower outcomes. In terms of the three key model parameters underlying the lender's enforcement decision, we estimate incremental fees of 0.45% of the loan amount, a reduction in the cost of default of 2.9% of the loan amount, and an increase in the rate of lender switching by the borrower of 29.6 percentage points. Incorporating the underlying estimating equations in a seemingly unrelated regression (SUR) framework and allowing for arbitrary correlations among the parameters, we estimate an average value of the lending relationship, from the lender's perspective, of 11.6% of the loan amount. This estimate is robust to various functional forms and bandwidths underlying the regression discontinuity design, controlling for borrower and loan characteristics, and the inclusion of various fixed effects.[2]

If our empirical approach captures the value of a relationship from the perspective of the lender, then we would expect our estimate to vary along the dimensions predicted by theories explaining the existence of these relationships. If the mechanism generating relationship value for the lender is due to an incumbent lender's informational advantage over a non-incumbent lender (Bharath, Dahiya, Saunders, and Srinivasan 2007), then we should see greater value of relationships when borrower opacity is high. We find that relationships where the borrower has high discretionary accruals, high analyst forecast dispersion, high goodwill, or high asset

[2] We also find estimates that are similar to our baseline using strategies to mitigate potential borrower manipulation of underlying covenant ratios and amounts.

intangibility are all associated with significantly greater relationship value. Similarly, a lender, through the natural course of lending to a firm, acquires proprietary information that it can exploit to charge a higher spread, holding up the borrower (Hauswald and Marquez 2006; Schenone 2010; Bird, Karolyi, and Ruchti 2019). The value of the relationship to the lender should then be higher for borrowers with fewer, or more costly, alternative sources of financing. We indeed find that relationships with borrowers that are more dependent on a particular lender are more valuable, whether we measure such dependence using an indicator variable for borrowing from only a single bank, a high loan-to-asset ratio, a poor credit rating or an uncompetitive local banking market. Finally, we estimate a higher relationship value for longer relationships and for those with greater opportunities for cross-selling.

We next use this cross-sectional variation to impute aggregate relationship capital for lenders based on the composition of their loan portfolios. That is, we apply the estimated average relationship value to the size of each loan portfolio, adjusting for the borrower heterogeneity in the value discussed above. At the lender level, in our sample relationship capital is equivalent to 6.6% of total assets or 41.2% of total capital (combining equity capital and relationship capital), with significant heterogeneity across lenders and over time. We also find evidence that relationship capital matters for bank valuation. Not only are market-to-book ratios and relationship capital correlated in levels, but changes in the market-to-book ratio are positively associated with changes in relationship capital, consistent with the market recognizing the importance of the underlying relationships as a form of intangible capital.

Our bank-level measures of relationship capital also vary in ways predicted by recent models of banking (Bolton, Freixas, Gambacorta, and Mistrulli 2016). In particular, relationship capital is negatively associated with lender size, but more relationship-intensive lenders tend to obtain more financing via long-term debt. Further, as one might expect, high relationship capital banks report relatively smaller loan loss reserves and have higher returns on equity. Finally, we explore trends in the importance of relationship capital over time. Traditional equity capital ratios have steadily climbed since the 1990s, with a not insignificant drop during the financial crisis of 2007-2009, followed by a swift recovery. However, while relationship capital ratios saw a similar drop through the crisis period, they have not subsequently recovered, which suggests that the financial crisis may have led to a significant and permanent destruction of value.

A long literature argues that the production of safe, liquid liabilities used for transactions creates value for banks (e.g., Gorton and Pennacchi, 1990). Our paper contributes to the related literature that focuses on bank value creation from the assets side of the balance sheet, which typically involves the information production role of banks (Leland and Pyle 1977; Diamond 1984; Ramakrishnan and Thakor 1984; Boyd and Prescott 1986; Allen 1990; Diamond 1991; Rajan 1992; Winton 1995; Shockley and Thakor 1997; Acharya, Hasan, and Saunders 2006; Su 2007; Allen, Carletti, and Marquez 2011).[3] To this literature, our goal is to contribute

[3] For a recent discussion of the relative contributions of the assets and liabilities sides of the balance sheet, see Egan, Lewellen, and Sunderam (2018).

a microfounded quantification of the contribution to bank value of asset-side information production.

A significant portion of the literature on bank lending has focused on relationships. Prior work has documented the consequences of relationship lending for borrowers in terms of credit access and contracting (e.g., Petersen and Rajan 1994; Berger and Udell 1995; Ioannidou and Ongena 2010; Gopalan, Udell, and Yerramilli 2011; Prilmeier 2017) and the borrower's investment, employment, and performance (e.g., Slovin, Sushka, and Polonchek 1993; Kang and Stulz 2000; Gan 2007; Chodorow-Reich 2014). Lenders seem to obtain more future syndication and underwriting business from relationship borrowers (e.g., Bharath, Dahiya, Saunders, and Srinivasan 2007; Drucker and Puri 2005, 2009) and are better able to maintain relationships outside of distress (e.g., Dahiya, Saunders, and Srinivasan 2003; Gopalan, Nanda, and Yerramilli 2011), but little else is known about the lenders' perspective of lending relationships. To this literature, we contribute a quantification of the value of lending relationships from the perspective of lenders.

Our paper also builds on the literature on the real effects of covenant violations. Prior work has documented the effects of covenant breaches on investment rates (Chava and Roberts 2008; Nini, Smith, and Sufi 2009), debt policy (Roberts and Sufi 2009a), executive turnover and payout policy (Nini, Smith, and Sufi 2012), employment (Falato and Liang 2016), board independence (Ferreira, Ferreira, and Mariano 2018), and internal resource allocation (Ersahin, Irani, and Le 2020). A more recent literature has developed exploring various determinants of the lender's decision to enforce a breach of covenant thresholds (Bird, Ertan, Karolyi, and

Ruchti 2020a,b; Chodorow-Reich and Falato 2019). Our paper extends this recent work by developing and estimating a simple model of the enforcement decision, incorporating the consequences of covenant violations.

We also contribute to the broader literature on measuring intangible capital. Our revealed preference approach departs from past studies that infer components of intangible capital by capitalizing current expenses at various discount rates (Griliches 1979; Lev and Sougiannis 1996; Hall, Jaffe, and Trajtenberg 2005; Xu 2008; Aw, Roberts, and Xu 2008; Bloom, Schankerman, and Van Reenen 2013; Gourio and Rudanko 2014; Warusawitharana 2015; Ewens, Peters, and Wang 2019).[4] Our approach depends on observing granular microdata on bank-borrower matched data, loan contracts, and the first order elements of the lender's enforcement decision tradeoff. In the lending relationship setting – as in other customer relationships – directly measuring the costs and benefits of relationships, even those that we can enumerate, is challenging because they are often not observed.[5] However, because lenders know the value that they assign to relationships and we observe their enforcement decisions, we can estimate a model of enforcement to uncover their revealed preference for relationships. We believe that our approach could be applied in settings outside of the banking industry with similar microdata on customer relationships.

[4] Doraszelski and Jaumandreu (2013) adopts a more flexible approach to estimating the stock of R&D, although in their model R&D expenditures shift the productivity Markov process.

[5] The complexity and measurement of the value of intangibles has long been a concern of accounting researchers and standard setters (e.g., Lev 2001; Skinner 2008; FASB ASU 2014-18). For example, this complexity subjects a firm's fair value estimates of intangibles to substantial noise (Ramanna and Watts 2012; Shalev, Zhang and Zhang 2013; Zhang and Zhang 2017; McInnis and Monsen 2017).

2 Theoretical Framework

In this section, we model a lender making the decision of whether or not to enforce a borrower's covenant breach. This decision entails several benefits and costs. On the benefit side, enforcement can generate waiver and amendment fees, and, by intervening in the operations of the borrower, the likelihood that the borrower defaults may be reduced.[6] However, enforcement may upset the lending relationship, perhaps because the lender is making a discretionary decision that hurts the borrower. This reduces the likelihood that the bank is able to make future loans to the borrower and enjoy whatever rents that entails.[7] Below, we outline a simple model of this tradeoff that we empirically estimate in Section 3.

Consider the case of the marginal enforcement decision on a borrower that is marginally in breach of a covenant. Let ϕ be the incremental fees charged and ω be the change in the expected cost of default when the lender enforces the violation. Furthermore, ψ is the change in the probability that the borrower switches away from borrowing from the lender in the future, i.e. the probability of relationship termination. Finally, let V be the present value of the lending relationship from the perspective of the lender, which is intended to capture all future rents from the relationship appropriately discounted both for time and for the risk that the relationship ends at some point in the future.

A lender then makes the decision to enforce on this borrower iff

[6] The lender could potentially derive additional benefits from renegotiating spreads and loan amounts though Bird, Ertan, Karolyi, and Ruchti (2020b) find that such benefits are second order relative to fees.

[7] We do not model any direct costs of enforcing the breach; in practice, covenant waivers and amendments typically include a provision reimbursing the lender for costs associated with the enforcement, such as legal fees.

$$\phi - \omega - \psi * V \geq 0 \quad (1)$$

This equation shows that a lender will enforce only if the incremental fees and reduced cost of default outweigh the increased chance of switching, and therefore the loss of V. For the marginal borrower, from the lender's perspective, marginal benefits should equal marginal costs so that

$$V = \frac{\phi - \omega}{\psi} \quad (2)$$

In other words, the value of a relationship is equal to the incremental fees charged to the borrower less the change in the expected cost of default, divided by the change in the probability that the borrower will switch lenders for the next loan. Theoretically, we would expect $\phi > 0$ to reflect positive fees extracted and $\omega < 0$ if enforcement brings about a decrease in the likelihood of default. Additionally, we expect that $\psi > 0$ as enforcing on the borrower increases the likelihood that the borrower will switch lenders, terminating the relationship. If these assumptions hold, then equation (2) shows that the value of a relationship should be positive. In the next section, our goal is to estimate this value empirically using observed covenant enforcement decisions.

3 Data and Empirical Strategy

3.1 Data

We require five primary data sources to construct our main estimation sample. These are the Center for Research in Security Prices (CRSP), Standard & Poor's Compustat, I/B/E/S, Federal Reserve Economic Data (FRED), and Thomson Reuters' DealScan. We obtain market data from CRSP, quarterly firm financials and S&P long-term issuer credit ratings from

Compustat, LIBOR rates from FRED, analyst forecast data from I/B/E/S, and loan details from DealScan. In addition to these primary sources, we match DealScan borrowers to firms in Compustat/CRSP using Michael Roberts' link table and we match lead lenders in DealScan to firms in Compustat/CRSP using Aytekin Ertan's link table. Finally, we rely on data shared by Greg Nini to identify material covenant violations (Becher, Griffin, and Nini 2018), and we collect data on covenant waiver and amendment fees from borrower 8-K filings following Bird, Ertan, Karolyi, and Ruchti (2020b).

The intersection of these data spans 1990 to 2016, but limited coverage in DealScan before 1996 means that the large majority of our sample follows 1996. Our sample ends in 2016 because Greg Nini's data on material covenant violations ends in that year. We also exclude borrowers from the financial and utilities sectors from our analysis.[8] These sample criteria and data requirements yield a sample of 5,908 distinct loan packages issued by 1,642 borrowers and 58 lenders, which we measure at the parent level. To measure borrower outcomes while these loan packages are outstanding,[9] we construct a borrower-quarter panel of observable characteristics, including metrics contracted upon in financial covenants, and match borrower-quarter observations to each quarter for which loan packages issued by that borrower are outstanding. For borrowers with contemporaneous outstanding loan packages, we retain duplicate borrower-quarter observations. We convert packages to loan package-quarters using

[8] Two-digit SIC codes between 60 and 69, and between 44 and 50, respectively.

[9] We opt for loan packages rather than tranches because covenants are defined at the package level, and for loan packages rather than the borrowing entity since the same borrower may have multiple loans outstanding from different lenders in a given quarter.

the stated start and end dates, which, after other data requirements, yields a total of 41,930 loan package-quarter observations.[10]

The running variable in our fuzzy regression discontinuity analysis is covenant slack, the standardized distance to pre-set covenant thresholds. Negative values of covenant slack indicate covenant breaches, regardless of whether the financial covenant involves a minimum or maximum threshold for the underlying financial ratio or amount. Our loan package-quarter panel includes data on the underlying financial ratios and amounts as well as the pre-set covenant thresholds, which allows us to calculate the slack of firm i's jth covenant in quarter t as:

$$Slack_{ijt}^{min} = \frac{u_{ijt} - \underline{u_{ijt}}}{\sigma_{ijt}} \quad (3)$$

for minimum covenants, such as minimum interest coverage ratio, and as:

$$Slack_{ijt}^{max} = \frac{\overline{u_{ijt}} - u_{ijt}}{\sigma_{ijt}} \quad (4)$$

for maximum covenants, such as maximum debt-to-EBITDA ratio. In these equations, u represents the underlying financial ratio or amount, $\underline{u}$ ($\bar{u}$) the minimum (maximum) covenant threshold, and σ the average past eight-quarter volatility of the underlying ratio or amount within a two-digit SIC industry.[11] To aggregate covenant slack observations across multiple covenants within a loan package, we code the minimum as *Slack*. As presented in Table 1, which focuses on a sample within 10σ bandwidth of the pre-set covenant thresholds, the average

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[10] We define package maturity as the stated maturity date of the largest tranche.

[11] Covenant threshold calculations are discussed in Appendix A.2 and are broadly in line with Demerjian and Owens (2016).

Slack is 1.067. We also construct *Breac*h, an indicator that equals one if *Slack* is less than zero. In this sample, 20.99% of loan package-quarter observations are in breach, which is consistent with prior literature (e.g., Chava and Roberts 2008, Chodorow-Reich and Falato 2020).

Because the definitions of financial metrics upon which covenants are written can vary across contracts, an important consideration in our analysis is measurement error (Zhang 2008; Demerjian and Owens 2016). The easily calculable ratios and amounts from borrower financial statements may not conform to contract-specific definitions, or the covenant thresholds may vary over time for reasons that are generally unobservable to the econometrician. A benefit of our fuzzy regression discontinuity design approach is that these sources of measurement error should not influence our estimates. Specifically, our approach identifies the marginal enforcement using the set of compliers – i.e., lenders that enforce based on the pre-set covenant thresholds that we observe – that are explicitly not explained by measurement error.

Our primary objective is to estimate the marginal effect of covenant enforcement on the propensity of the borrower to switch lenders and on the expected cost of default, through reduced risk-taking, for example (Chava and Roberts 2008). For this, we need a measure of enforcement. Our proxy for enforcement, which we label *Enforcement*, is an indicator for package-quarter observations with material covenant violations identified in data collected by Greg Nini. These material covenant violations are observable because SEC disclosure rules (17 CFR 210.4-08 "General Notes to Financial Statements") require borrowers to disclose both breaches of covenant thresholds that exist at the time of the filing as well as cured breaches, such as through covenant waivers or loan amendments, associated with material consequence, such as waiver or amendment fees, within four quarters. In our sample presented in Table 1, 5.2% of package-quarter observations have had a material covenant violation. When combined with information about covenant breaches, these material covenant violations imply an average enforcement rate of about 24.6%, which is quantitatively consistent with average enforcement rates reported in related work using the Shared National Credit supervisory data from the Federal Reserve, FDIC, and Office of the Comptroller of the Currency (e.g., Chodorow-Reich and Falato 2019).

3.2 Decision inputs estimation

Because our strategy is based on marginal enforcement by lenders, we must find an empirical setting in which lenders make this decision. Specifically, we estimate models of changes in expected default costs and the probability of retaining a borrower using an instrument for enforcement. Our instrument is the incidence of a covenant breach, which determines the transfer of control rights and the discretion to pursue some form of corrective action to the lender. By controlling for the level of slack in a borrower's covenants flexibly on each side of the breach threshold, we can therefore measure the marginal enforcement of covenants by lenders controlling for underlying borrower quality.

3.2.1 Marginal enforcement

To identify the effects of the marginal covenant enforcement on expected default costs and relationship termination, we implement a fuzzy regression discontinuity design based on pre-set covenant thresholds. When the borrower breaches a covenant threshold (e.g., by exceeding a maximum threshold, such as a Debt/EBITDA covenant), the lender can enforce the breach by requiring fees, amendments to loan terms, and/or operational concessions to reduce default risk. For publicly-listed borrowers in our sample, we observe the distance to covenant violations (*Slack*), covenant breaches (*Breach*), and enforcement actions (*Enforce*). The difference in enforcement rates just-above versus just-below the borrower's pre-set covenant thresholds, where $Slack = 0$, identifies marginal covenant enforcement. To isolate breach-driven variation in covenant enforcement, we estimate the following regression discontinuity design

$$Enforce_{ikt} = \eta + \lambda * Breach_{ikt} + F(Slack_{ikt}) + G(Slack_{ikt}) + \delta_{ikt} \quad (5)$$

where i, k, t are borrower, lender, and time, respectively. $F(\cdot)$ and $G(\cdot)$ are flexible polynomial functions of $Slack_{ikt}$. The quantity of interest is λ, the increase in enforcement rates at the pre-set covenant thresholds.

3.2.2 Fees

Estimating the fee component is the simplest part of our procedure. Because enforcing the contractual obligations relevant to a covenant violation is often accompanied by waiver or renegotiation fees, we simply calculate the mean and standard deviation of these fees using a sample of hand-collected fees from material covenant violation disclosures. We plot a kernel of fees charged to enforced-upon borrowers in Figure 1, finding that while there is some variation in the fees charged, the fees on average equal 0.45% of loan principal.

3.2.3 Change in expected cost of default

The second decision input is the extent to which the lender can influence the likelihood and cost of default by enforcing a covenant breach, through imposing changes in borrower behavior (see, e.g., Chava and Roberts 2008). Specifically, we are interested in finding an empirical analog to ω, the change in the expected cost of default. To do so, we must both calculate the expected cost of default and estimate a model of the effect of enforcement on this cost. Within a loan contract, there is typically a stream of payments to the lender that can be discounted according to the spread plus LIBOR of the loan, or the risk-compensated time value of money for that particular borrower. For loan principal P, spread plus LIBOR r, and time to maturity T, the expected payment, without default, is

$$Payment_{NoDefault} \equiv \frac{r * P}{(1+r)} + \frac{r * P}{(1+r)^2} + \frac{r * P}{(1+r)^3} + \cdots + \frac{(1+r) * P}{(1+r)^T} \tag{6}$$

which has the net present value of P.

We model default as a likelihood of defaulting on payments in year τ, δ_τ, such that $\delta_{\tau+1} \geq \delta_\tau$ (If a firm in fact defaults, it defaults on subsequent payments as well) and a value of recovery, conditional on default, RCD. To avoid writing down a complicated series, we present the expected payments with default as

$$Payment_{WithDefault} = \sum_{\tau=1}^{T} \frac{(r * P)(1-\delta_\tau)}{(1+r)^\tau} + \sum_{\tau=1}^{T} \frac{RCD * (\delta_\tau - \delta_{\tau-1})}{(1+r)^\tau} + \frac{P(1-\delta_T)}{(1+r)^T} \tag{7}$$

The expected cost of default with no enforcement is therefore

$$ECD = \ Payment_{NoDefault} - \ Payment_{WithDefault} \tag{8}$$

We use data on ex post default events (i.e., credit ratings of "D" or "SD") from S&P long-term credit ratings, LIBOR from FRED, and recovery rate estimates for secured (69.5%) and unsecured (52.1%) private loans from Carty, Gates, and Gupton (2000) to calculate *ECD* for each loan package-quarter observation. Using observed subsequent default events makes the calculation of *ECD* deterministic, but allows us to retain the ability to compare default outcomes for borrowers experiencing covenant enforcement and non-breaching borrowers. We calculate *ECD* as

$$ECD = \sum_{\tau=1}^{T} \frac{(1 - RCD_{\tau})}{(1+r)^{\tau}} \tag{9}$$

where $RCD_{\tau} = RCD$ if default occurs in year τ and 1 otherwise, and we write the change in *ECD* resulting from behavior in year t as $\Delta ECD = ECD_{t+1} - ECD_{t}$. If the marginal covenant enforcement alters the borrower's behavior, then we expect that the change in *ECD* will be lower for borrowers just-breaching their covenant thresholds relative to those just–exceeding them.

We estimate the marginal effect of covenant enforcement on changes in the expected cost of default using the following model,

$$\Delta ECD_{ikt} = \alpha + \beta_{ECD} * \widehat{Enforce}_{ikt} + F(Slack_{ikt}) + G(Slack_{ikt}) + \epsilon_{ikt} \tag{10}$$

$$Enforce_{ikt} = \eta + \lambda * Breach_{ikt} + F(Slack_{ikt}) + G(Slack_{ikt}) + \delta_{ikt} \qquad \text{(5, repeated)}$$

where i, k, t are borrower, lender, and time, respectively. $F(\cdot)$ and $G(\cdot)$ are flexible polynomial functions of $Slack_{ikt}$ and $\widehat{Enforce}_{ikt}$ is instrumented enforcement. The quantity of interest, that we use to measure the change in the expected cost of default, ω, is β_{ECD}.

3.2.4 Change in likelihood of relationship termination

Another decision input is the propensity for the borrower to terminate the lending relationship by switching lenders for subsequent loans. Prior work has documented evidence that borrowers are more likely to switch lenders following an episode of covenant enforcement when the lender chose to enforce based on income-seeking incentives (Bird, Ertan, Karolyi, and Ruchti 2020b). We extend this evidence to show that borrowers are more likely to switch lenders following covenant enforcement irrespective of the lenders' motives for enforcement. We define $Switch_{ikt}$ as an indicator variable that equals one if borrower i's next loan is with a lender other than lender k. We estimate the effect of enforcement on the likelihood of switching using the following model,

$$Switch_{ikt} = \alpha + \beta_{Switch} * \widehat{Enforce}_{ikt} + F(Slack_{ikt}) + G(Slack_{ikt}) + \epsilon_{ikt} \tag{11}$$

$$Enforce_{ikt} = \eta + \lambda * Breach_{ikt} + F(Slack_{ikt}) + G(Slack_{ikt}) + \delta_{ikt} \tag{5, repeated}$$

where i, k, t are borrower, lender, and time, respectively. $F(\cdot)$ and $G(\cdot)$ are flexible polynomial functions of $Slack_{ikt}$ and $\widehat{Enforce}_{ikt}$ is instrumented enforcement. The quantity of interest, that we use to measure the increased likelihood of switching lenders, ψ_{ik}, is β_{Switch}.

3.3 Estimating the value of relationships

We next set up our estimation of the value of a relationship between lender k and borrower i, $V(\gamma_{ik})$, where γ_{ik} are the borrower and lender characteristics. Because the value of a relationship should vary with match-specific attributes, we are implicitly estimating the value of the relationship between lender k and borrower i as a function of those attributes. We combine the estimates generated in Section 3.2 in a seemingly unrelated regression framework to solve for the value of a relationship for the marginal enforcement. From equation (2), we have that

$$V(\gamma_{\bar{i}k}) = \frac{\phi - \omega}{\psi} \tag{2, repeated}$$

The empirical equivalent is therefore

$$VOR = \frac{\hat{\beta}_{Fees} - \hat{\beta}_{ECD}}{\hat{\beta}_{Switch}} \tag{12}$$

To produce unbiased estimates of *VOR* and to calculate standard errors, we perform bootstraps over 10,000 samples. That is, we draw a new sample with replacement, denoted by superscript s, and then estimate β^s_{Fees}, β^s_{ECD}, and β^s_{Switch} for each bootstrapped sample. For each bootstrapped sample, we can therefore calculate a sample value of relationships, VOR^s, or value of relationships. Specifically, the mean and standard deviation are as follows:

$$VOR_{Bootstrap} = \sum_{s=1}^{S} VOR^s \tag{13}$$

$$std(VOR)_{Bootstrap} = \sqrt{\sum_{s=1}^{S} \frac{(VOR^s - VOR_{Bootstrap})^2}{S-1}} \tag{14}$$

The bootstrapping procedure satisfies three objectives in our estimation. The first is naturally to produce standard errors for the value of relationships through simulation. The second objective is to correct for any effects of heterogeneity in estimates of the three components of the value of relationships, ϕ, ω, and ψ_{ik} on the nonlinear transformation of these scalar primitives. That is, through using simulation, variation in β^s_{Fees}, β^s_{ECD}, and β^s_{Switch} will produce nonlinear variation in VOR^s. This will therefore remove any bias that simply calculating *VOR* by implementing equation (12) as a function of $\hat{\beta}_{Fees}$, $\hat{\beta}_{ECD}$, and $\hat{\beta}_{Switch}$ would induce. Finally, bootstrapping allows us to correct for any correlations in the errors of $\hat{\beta}_{Fees}$, $\hat{\beta}_{ECD}$, and $\hat{\beta}_{Switch}$, thus directly addressing a fundamental assumption in our modeling of this problem, that the errors in the equations underlying $\hat{\beta}_{Fees}$, $\hat{\beta}_{ECD}$, and $\hat{\beta}_{Switch}$ are uncorrelated.

4 Results

4.1 Model inputs

We start this section by discussing the results of estimating the three primitives of the model separately, and then move on to the results of combining these primitives to get an estimate of the value of a lending relationship. The first model primitive that enters the lender's covenant enforcement tradeoff are waiver fees. To estimate the enforcement benefits of covenant waiver fees, we simply calculate the average waiver fee using hand-collected data from SEC Form 8-K filings as described in Section 3. In Figure 1, we plot the distribution of waiver fees charged by lenders that enforce a covenant breach. As reported in Table 1, the average waiver fee is 0.45% of loan principal, but we observe waiver fees in excess of 4.00% in our sample.

The second primitive of the enforcement tradeoff is the change in expected cost of default. We estimate the change in the expected cost of default due to incremental enforcement behavior by lenders using equation (10), in which we instrument for enforcement using equation (5). As before, the fuzzy regression discontinuity design ensures that the enforcement we study reflects the tradeoff between costs and benefits rather than selection on some observable or unobservable characteristics of the covenant-breaching borrowers.

Table 3 provides estimates of equation (10) using several alternative specifications. Our dependent variable is ΔECD, the forward-looking change in the expected cost of default. We instrument for *Enforcement* using the covenant breach cutoff in the running variable covenant *Slack*, defined in equations (3) and (4). In all columns, we select bandwidths that are close to the optimal bandwidths as determined in Calonico, Cattaneo, and Titiunik (2014), but rounded so that we can consistently use the same combinations of bandwidths and polynomial control functions across dependent variables.[12]

In column (1) of Table 3, we use no polynomial control functions and a bandwidth of one unit of *Slack* and find that the marginal enforcement is associated with a decrease in the expected cost of default of 3.5% of the loan principal, on average. In column (2), our preferred specification, we include linear control functions and a bandwidth of five units of *Slack* and find a slightly lower effect of a 2.9% decrease in the expected cost of default. We find quantitatively similar results to our preferred specification when we include quadratic or cubic polynomials and wider bandwidths in columns (3) and (4), indicating that tighter bandwidths and linear control functions are sufficient for identifying the local average treatment effect of covenant enforcement on borrower outcomes. These estimates are similar in magnitude to those implied by the graphical evidence in Figure 3.

These findings indicate that enforcement of the consequences of contractual breaches are associated with significant decreases in the expected costs of default to the lender. Whether

[12] Our results are slightly larger when using the optimal bandwidth selection procedure (See Panel B of Table B2 in Appendix B).

these are due to decreased risk of the loan due to altered terms (e.g., Roberts and Sufi 2009) or to implicit or explicit changes in borrower behavior (e.g., Chava and Roberts 2008), this is a clear benefit of enforcing the covenant breach to the lender. Given that this benefit will be divided by switching rates and that enforcement of covenants in these contracts is quite uncommon (Bird, Ertan, Karolyi, and Ruchti 2020a) it is clear by revealed preference that lenders place a value on lending relationships that is weakly greater than 2.9% of the loan principal.

The third primitive of the enforcement tradeoff is the probability of relationship termination, which we measure using the incidence of the borrower selecting a different lender for subsequent loans. We present our estimates for the induced increase in switching rates due to incremental enforcement behavior by lenders using the same fuzzy regression discontinuity design described above and in equation (11). Table 4 provides estimates of equation (11) using several alternative specifications. Our dependent variable is *Switch*, an indicator that equals one if the borrower switches to a new lead bank on its next loan and zero otherwise. We instrument for *Enforcement* using the covenant breach cutoff in the running variable covenant *Slack*, defined in equations (3) and (4).[13]

In column (1) of Table 4, we use no polynomial control functions and a bandwidth of one unit of *Slack* and find that an incremental enforcement is associated with an increase in the

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[13] As in our analysis of ΔECD, we select bandwidths to be close to the optimal bandwidths determined by methods in Calonico, Cattaneo, and Titiunik (2014), but we round them to maintain consistency across combinations of bandwidths, polynomial control functions, and dependent variables. Similar to the results for ΔECD, our switching rate estimates are slightly larger when using the optimal bandwidth selection procedure (See Panel A of Table B2 in Appendix B).

switching rate of 0.312, or 31.2 percentage points, on average. In column (2), our preferred specification, we include linear control functions and a bandwidth of five units of *Slack* and find a slightly lower effect of a 0.296 increase in the rate at which a borrower will switch lead arrangers for their next loan. We find quantitatively similar results to our preferred specification when we include quadratic or cubic polynomials and wider bandwidths in columns (3) and (4), indicating that tighter bandwidths and linear control functions are sufficient for identifying the marginal effect. As above, these estimates are similar in magnitude to those implied by the graphical evidence in Figure 4. Our primary takeaway from this analysis is that borrowers are about 30 percentage points more likely to terminate a lending relationship following covenant enforcement.

These findings are consistent with borrowers being disgruntled by incremental enforcement of the consequences covenant violations. This is consistent with Bird, Ertan, Karolyi, and Ruchti (2020b), which finds, in a similar setting, that enforcement driven by short-termism is associated with an increase in switching rates. This outcome is quite costly to an incumbent lender, as relationship value depends on the ability to use the relationship to generate future business (Bharath, Dahiya, Saunders, and Srinivasan 2007).

4.2 Value of relationships

The previous section describes our estimation approach for the individual components of the lender's enforcement tradeoff. We now incorporate these individual components into an estimator for the value of lending relationships using our analytical model. First, we reproduce the empirical analog to the value of relationships equation (2) here,

$$VOR = \frac{\hat{\beta}_{Fees} - \hat{\beta}_{ECD}}{\hat{\beta}_{Switch}} \qquad \text{(12, repeated)}$$

We know that the incremental fees that can be charged to borrowers by enforcing lenders, $\hat{\beta}_{Fees}$, is 0.45% of loan principal. Using linear control functions and a reasonably tight bandwidth in column (2) of Table 3, we show that the expected change in the expected costs to the lender of a borrower's default, $\hat{\beta}_{ECD}$, are -2.9% of loan principal. Finally, in column (2) of Table 4, we show that the expected change in switching rates for borrowers who are incrementally enforced upon is 0.296. These three quantities are presented in columns (1), (2), and (3), respectively, of Table 5. Using these inputs and equation (12), we can solve for the value of a relationship in percent of loan principal, on average, $VOR = (0.447\% - (-2.901\%))/0.296$, which computes to 11.3%, as is shown in column (4) of the table. In this case, standard errors are computed by a simple bootstrapping procedure that treats the estimates of each parameter as independent.

However, there are two assumptions made in our analysis in column (4) of Table 5 that should be addressed to ensure that we are finding both unbiased estimates and precise standard errors. The first is that equation (12) is a nonlinear function of the underlying $\hat{\beta}_{Fees}$, $\hat{\beta}_{ECD}$, and $\hat{\beta}_{Switch}$. Even if the errors in our estimating equations are independent, variation in estimates should produce nonlinear variation in our calculation of VOR, which could bias our findings. Secondly, up to this point, we have assumed that the errors in the estimates of the individual components of the lender's tradeoff are independent.[14] Both nonlinearity and lack of independence could also in principle inflate or deflate our standard errors for the calculation of *VOR*.

We relax both of these assumptions using a bootstrapping procedure as described in Section 3.3. To find the coefficient we report in column (5) of Table 5, we average the calculated *VOR* estimates across 10,000 samples, also calculating standard errors from the 10,000 *VOR* estimates (See equations 13 and 14). By using bootstraps, any variation in estimates of $\hat{\beta}_{Fees}$, $\hat{\beta}_{ECD}$, and $\hat{\beta}_{Switch}$ will flow through to each sample's *VOR* estimate. Moreover, variation across samples will uncover any correlation in the errors of our estimating equations.

We find that nonlinearity in the *VOR* function and correlation across parameter estimates does not significantly bias our original result. Our preferred estimate of the value of lending relationships, which corrects for these correlations across estimates, is 11.6% of loan principal. The standard errors remain qualitatively similar to the uncorrected estimates. This indicates that while nonlinearities and independence may be econometrically relevant in theory, they are not empirically important in this setting. Nevertheless, we adopt this bootstrapping procedure in all of our subsequent analysis, making column (5) of Table 5 our baseline specification.

[14] In Appendix Table C1, we show using bootstrap simulations that there is very little correlation across our estimates of the model primitives.

4.3 Robustness

In previous sections, we have shown evidence of the robustness of our estimates of the model primitives to various combinations of bandwidth and polynomial control functions. In this section, we investigate the robustness of our estimates of the *VOR* to various functional form choices, defining the running variable – covenant slack – using only the subset of covenants for which the underlying ratios are not manipulated, sample selection choices, and potential sources of heterogeneity. Across these econometric choices, we obtain similar estimates to our preferred specification in column (5) of Table 5.

In row (1) of Table 6, we report our results from Table 5 for the change in the expected cost of default, switching rates, and fees, along with our nonlinearity- and independence-adjusted preferred estimate for *VOR*, now in column (4). In each subsequent row, we estimate the model with alternative econometric choices. We first explore functional form robustness, and find quantitatively similar estimates when we replace our preferred linear polynomial control functions with quadratic or cubic ones. This may not be surprising given the stability of our estimates of the model primitives $\beta_{\Delta ECD}$ and β_{Switch} across specifications in Table 3, Table 4, and Appendix Table B2. In rows (4)–(6), we use local linear, quadratic, or cubic control functions with the Epanechnikov kernel, and we again find quantitatively similar estimates.

In rows (7)-(9), we present estimates using linear, quadratic, and cubic polynomials, respectively, using an alternative definition of covenant slack based only on covenant types for which McCrary (2008) tests reveal no evidence of manipulation. Our estimates in these specifications are slightly larger, ranging from 12.1% to 13.1%, which suggests that covenant ratio manipulation adds attenuating measurement error to our estimates. In row (10), we impute waiver fees based on a flexible cubic polynomial function of breach severity to account for the subsample used to calculate fees, and find quantitatively similar estimates to our baseline estimates. In row (11), we restrict the sample to loan-quarter observations for which we observe both switching and changes in the expected cost of default, which reduces the sample in our preferred switching specifications since these observations are now required to have non-missing data on S&P long-term credit ratings. In row (12) we remove the last two years from our estimates, and in row (13) we remove the first two years from our sample, and we obtain slightly larger estimates than in our preferred specification. ows (12) and (13) indicate that our results are not driven by data errors or selection on switching rates from the early or late parts of our sample.

The remainder of Table 6 is focused on potential sources of observable and unobservable heterogeneity in the value of relationships. In row (14), we first control for market-to-book ratio, market capitalization, and initial covenant strictness. In rows (15)-(18) we include fixed effects at the industry, calendar-quarter, lender, and borrower levels, respectively. In each of these five rows, we obtain estimates that are the same sign and qualitatively similar in magnitude to our preferred specification. In cases in which the estimates diverge from our preferred estimates, they tend to be larger in magnitude. These findings indicate that our preferred estimates are not driven by time-varying observable characteristics of borrowers and loans, time-invariant unobservable characteristics of the borrower or lender, or secular trends.

Overall this subsection indicates that our measurements are robust to a variety of reasonable alternative econometric choices. In particular, our results are unlikely to be driven by statistical artifacts embedded in the methodology, changes in the population of loans over time, or characteristics of borrowers, lenders, or loans. These findings are therefore consistent with lenders placing value on the relationships they hold with borrowers, but they also indicate that our methodological approach delivers stable estimates of the value of relationships.

5 Applications

5.1 What drives the value of relationships?

If our empirical approach captures the value of a relationship from the perspective of the lender, then we would expect our estimate to vary along the dimensions predicted by theories explaining the existence of these relationships. For example, if the mechanism generating relationship value for the lender is based on the informational advantage the incumbent has over non-incumbent lenders (Bharath, Dahiya, Saunders, and Srinivasan 2007), then we should see greater value of relationships when borrower opacity is high. This informational advantage should be more pronounced for more opaque borrowers, and we therefore expect to see a higher relationship value for such borrowers. Similarly, the incumbent lender can use this informational advantage to hold up the borrower and collect more profits on the loan (Hauswald and Marquez 2006; Schenone 2010; Bird, Karolyi, and Ruchti 2019). This hold up problem should be more serious when a borrower has fewer alternative sources of financing. We therefore expect a higher relationship value for these types of borrowers. We investigate these related mechanisms by splitting our sample into subsamples based on these borrower characteristics and then comparing estimates across the samples.

In Table 7, we explore the role of borrower opacity on value of relationships. We present in each row estimates for ϕ, representing incremental fees, ω, the change in the expected cost of default, ψ, the incidence of relationship termination, and *VOR*, the estimated relationship value, following the specifications presented in Table 5, columns (1), (2), (3), and (5). As before, the *VOR* estimates are calculated using bootstrapped samples (for each subsample).

For each set of cross-sectional tests, we use a binomial test for the proportion of samples in which the parameter estimates are different in the expected direction. In rows (1) and (2), we start by proxying for borrower opacity using discretionary accruals, as defined in Teoh, Welch, and Wong (1998). In this case, high opacity borrowers are those with discretionary accruals above the sample median. We find that high opacity (i.e. high discretionary accruals) borrowers are associated with greater *VOR* in the sense that we can reject the null hypothesis that *VOR* is equal in the two subsamples with a p-value of less than 0.001.

Next, in rows (3) and (4), we use analyst dispersion as our proxy for borrower opacity, where high opacity is defined as having analyst forecast dispersion above the sample median. Forecast dispersion likely reflects borrower opacity to the extent that uncertainty over the borrower's performance or financial state drives disagreement among information intermediaries. Consistent with the first two columns, we again find that high opacity borrowers yield more valuable relationships. In the remaining four rows, we follow the same procedure using the level of the borrower's goodwill and the borrower's asset intangibility, based on the idea that borrowers with high levels of goodwill (due to acquisitions) and high levels of intangible assets are more difficult for outsiders to understand and value. Again, we find results consistent with higher relationship value for more opaque borrowers. Notably, we find a higher value of relationships in these cases even though it is also possible that screening and monitoring these kinds of borrowers is relatively more costly.

In Table 8, we further explore the role of hold up in how lenders value their relationships with borrowers. As in Table 7, each row presents estimates for each of the three inputs and for the value of relationships, *VOR*, following the specifications from columns (1), (2), (3), and (5), respectively, of Table 5. In rows (1) and (2) of Table 8, we separately investigate relationships with borrowers with low and high loan-to-asset ratios, which should be related to the extent of the borrower's reliance on this particular relationship for its overall financing needs. We find that lenders place more value on relationships with borrowers with above median ratios of loan to assets, and this difference in our estimates is unlikely ($p<0.001$) to occur by chance, according to a binomial test of proportions. By similar logic, if a borrower only borrows from a single bank, i.e. has only a single relationship, then it should be more dependent on that bank. In rows (3) and (4), we find that lenders place greater value on these exclusive relationships than they do relationships with borrowers borrowing from multiple banks.

In the next four rows of Table 8, we explore variation in the borrower's outside options. In rows (5) and (6), we find that lenders place greater value on relationships with borrowers with below median credit ratings, and so with less access, or more costly access, to alternative sources of financing. In rows (7) and (8) we investigate the role of outside options through the lens of the competitiveness of the local banking market. As expected, we find that lenders place greater value on relationships with borrowers when there is otherwise less lending activity in that borrower's metropolitan statistical area or industry, suggesting a less competitive local banking market and so more restricted alternatives for the borrower. Finally, we investigate whether the lender differentially values relationships of different lengths, and find this is indeed the case. Specifically, in rows (9) and (10), we show that lenders place greater value on longer relationships. One possible explanation for this finding relates to the importance of asymmetric information between the incumbent and non-incumbent lenders discussed above. If this informational advantage is derived exactly from the lender's experience with the borrower, then it should grow with the length of the relationship. This result is also consistent with lenders' optimally managing their portfolio of lending relationships in the face of constrained effort or ability to monitor many borrowers – the relationships that the lenders works to maintain are those generating more value. The final set of results in the table provides further evidence on this point. In rows (11) and (12), we find that lenders value relationships more when there is more potential for cross-selling (Drucker and Puri 2005), which we define as the borrower having outstanding loans of multiple types and tranches. In such cases, the lender would have more opportunity to generate rents from the relationship.

5.2 Generalizability

In our remaining applications, we apply our estimates of the value of relationships to calculate total relationship capital at the bank level. Before doing so, it is important to consider two possible biases related to our estimation procedure. The first concerns a feature of the theoretical framework. Technically, what we estimate is an upper bound in the sense that lenders derive rents from their enforcement behavior. Such rents would imply that the cost of enforcement, which is related to the value of the relationship, is strictly less than the benefits. However, as long as the borrowers that are on the margin of breaching covenants are also the borrowers on the margin of covenant enforcement, then the estimates we describe in Section 5 should be reasonably tight upper bounds. We believe that this condition is both intuitive and consistent with the strong empirical relationship between breach severity and enforcement propensity as shown in Figure 2.

The second potential concern for generalizing our estimates is selection. Namely, it may be the case that borrowers that end up close to their pre-set covenant thresholds are different than the lender's average borrower; most importantly, the value of the respective relationships may not be the same to the lender. For several reasons, we do not believe that the difference in the value of relationships for these two groups of borrowers is large. Most importantly, breaching covenants is quite common; Table 1 reports that 21% of borrowers are in breach of at least one covenant threshold at a given time, on average. This implies that the borrowers that are on the margin of breaching covenants are unlikely to be different ex ante from the average borrower. Specifically, we note two additional supporting empirical facts. First, borrower characteristics at loan initiation have very limited predictive power for future breaches (Figure 6), and second, borrower characteristics are smooth around the threshold (Figure 5).

Notwithstanding these arguments, it is still possible that by the time of breach, the borrower has evolved to become meaningfully different from the representative borrower. For example, it could be the case that the value of having a relationship with the borrower changes by the time of a breach, though, theoretically, the value could move in either direction. A breaching borrower might be a less valuable relationship partner if its viability is in question. On the other hand, based on the result discussed in the previous subsection, such a borrower might be in a worse bargaining position and so be more susceptible to lender hold up.

To investigate the nature of this potential selection bias, we can use the heterogeneity estimates from Tables 7 and 8. The borrower characteristic median splits on which those results are based are defined using the full sample, whereas the identifying variation comes from a subset of borrowers which may come predominantly from one side of the distribution or the other. If we want instead to get a more representative relationship value for the whole distribution, we can average these estimates, since 50% of observations in the full distribution will be below the median and 50% above. Using this method, we can produce a "centered" estimate of the value from each one of the borrower characteristics. This produces a range of estimates from 10.4% to 17.1%, with a mean of 13.6%. This range includes our main estimate of 11.6%, and indicates a relatively small potential downward bias due to selection. As such, these findings imply that, if anything, our remaining results in this section concerning the empirical importance of relationship capital are likely to be conservative.

5.3 What is the magnitude of relationship capital?

Having established the potential to generalize our findings to lenders' broader loan portfolio, our goal in this subsection is to use the cross-sectional variation in value estimated in Section 5.1 to impute aggregate relationship capital for each bank in our sample. Rather than assume that all banks value their relationships in the same way, the idea is to use observed heterogeneity in loan portfolios as a simple way to adjust the value based on the characteristics of each loan portfolio. For each lender, we take each loan in DealScan for which it is the lead arranger and classify it into two groups, based on whether it is above or below the median on each of the dimensions studied in Tables 7 and 8. We then impute a value for that particular relationship by averaging the estimates from each group. We arrive at a bank-level value by adding up the relationship value for each of the bank's loans in DealScan, as a percentage of loan principal. Finally, we extend this relative value, as derived from the universe of DealScan loans, to the bank's total loan book, as disclosed in call reports. This total varies as the size and composition of the bank's loan portfolio changes from year to year.

In Figure 7, we plot a histogram of the relationship capital ratio, defined as the bank-level relationship capital defined above, divided by the bank's total assets. By design, this ratio is analogous to the traditional equity capital ratio for the bank. On average, the relationship capital ratio is 6.6%, which is similar in magnitude to the average equity capital ratio. The relationship capital ratio exhibits considerable variation with a 10^{th} percentile of 3.6% and a 90^{th} percentile of 9.2% - this is suggestive of substantial differences in the business models employed by different banks on the spectrum of transaction banking to relationship banking. In particular,

Figure 7 shows a bimodal distribution, consistent with a small number of lenders specializing in transactional, or low-relationship capital, lending.

To better understand the relationship capital ratio, in Figure 8, we present bin scatter plots of relationship capital ratios with lender-level characteristics. In subplot (a) of the figure, we see that larger lenders tend to have lower relationship capital, on average, whereas smaller lenders appear to specialize in high value lending relationships. In subplot (b), we find that high relationship capital lenders rely less on short-term debt financing, perhaps suggesting that lenders specializing in these relationships require more flexibility in their financing, and so rely less on debt that must be rolled over at the discretion of another lender. In other words, long-term relationships necessitate long-term financing. In subplot (c) of Figure 8, we find no statistically significant relationship between relationship capital and the bank's return on equity. However, we do find a statistically significant relationship between relationship capital ratios and equity capital ratios in subplot (d). In combination with subplot (a), this implies that large lenders tend to have lower equity capital ratios and also focus less on relationship lending.

We next turn to the time series behavior of relationship capital. It is well known that equity capital ratios are subject to both large shocks as well as secular trends – the financial crisis of 2007-2009 saw a substantial drop in the ratio of equity capital to total assets, but otherwise the trend since the 1990s has been positive. This is evident in subplot (a) of Figure 9, in which we plot bank equity capital ratios over the course of our sample with 95% confidence intervals. Focusing on the crisis period, there was a substantial drop in equity capital ratios from the middle of 2007 to early 2009, but this was followed by a steep increase in the following year.

Just as equity capital ratios fall as asset prices fall during a financial, relationship capital ratios should fall as well, though for somewhat different reasons. As lenders and borrowers are less able, or willing, to consummate new loans, lending relationships are destroyed and the relationship capital is destroyed with it. We show in subplot (b) of Figure 9 that there was a substantial drop in relationship capital ratios over the course of 2008; however, unlike equity capital, relationship capital has not subsequently rebounded. In fact, relationship capital fell during the financial crisis and has stayed at roughly the same level since. This could be due to changes in the types of loans lenders make, or potentially a shift in lending to non-regulated financial institutions. Regardless of the exact mechanism, this evidence is consistent with a structural shift in lending following the crisis.

5.4 Is relationship capital valuable?

Following the logic of the theoretical framework laid out in Section 2, our estimate of the value of relationships depends on the lender's enforcement choice and so reflects the lender's perception of this value. In our final set of tests, we investigate the extent to which these relationships are valued by the capital markets. That is, does relationship value translate to bank value? Our goal is both to further investigate the empirical importance of relationship capital and to validate our estimation strategy; since we measure relationship capital using observable lender behavior, we would expect that the market should also be able to interpret this information. To start, in Figure 10, we produce bin scatter plots of market to book ratios, i.e. bank value, and relationship capital ratios. Subplot (a) shows the relationship in levels and subplot (b) illustrates first differences. We see that higher levels of market to book are associated with higher levels of relationship capital, consistent with the market valuing relationship capital. Moreover, increases in relationship capital are associated with increases in market to book ratios, providing evidence against an alternative explanation of some fixed bank-specific factor or characteristic that leads to both higher measured relationship capital and a higher market to book ratio.

We accompany these univariate findings with a series of tests presented in Table 9. In column (1), we first show the univariate correlation and find that it is statistically significant at the 1% level. In column (2) we add fixed effects for calendar-quarter and in column (3) we include bank fixed effects, analogously to subplot (b) of Figure 10. We finally include controls for the bank's equity capital ratio and the natural log of its total assets in column (4). In all specifications, we find a positive correlation that is statistically significant at conventional levels. In particular, controlling for equity capital and size does not diminish the relationship. This is important given the strong underlying correlations of these variables with relationship capital depicted in Figure 8, and the likelihood that these characteristics are directly related to bank value. Overall, this graphical and statistical evidence suggests that markets recognize and value the intangible capital associated with a bank's lending relationships.

6 Conclusion

In this paper, we develop and estimate a simple model of a lender's decision to enforce breaches of pre-set covenant thresholds. Since a key part of this model is that enforcing leads to an increased risk of relationship termination, observing lenders' decisions on the margin allows us to infer the value that lenders place on their relationships. We find an average relationship value to the lender of 11.6% of the loan principal. As would be predicted by theories of lender hold up, we estimate that relationships with more opaque borrowers and those with fewer outside options are relatively more valuable.

Using the characteristics of each bank's loan portfolio, we use the heterogeneity in value to compute the bank-level total value of relationship capital. This intangible capital is approximately 6.6% of total assets (as measured on the balance sheet) or 41.2% of total capital, which combines traditional equity capital and our estimate of relationship capital. The importance of relationship capital varies significantly across banks, consistent with differences in business models, and over time. For example, nearly a quarter of aggregate relationship capital was lost in the Great Recession, and, in contrast with equity capital, relationship capital has not recovered. Finally, we show that banks' market-to-book ratios are positively associated with relationship capital in both levels and changes. This implies that the market recognizes and values the intangible capital derived from lending relationships.

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Appendix A. Data Sources and Definitions

Table A1. Variable Definitions

Variable	Definition	Data Source(s)
Enforcement	Indicator that equals 1 if the borrower reports a material covenant violation in any of the subsequent four quarters and zero otherwise.	Greg Nini
Slack	The minimum standardized distance to the pre-set covenant threshold in the loan contract. See Section 3.1 for details.	Compustat, DealScan
Breach	Indicator that equals 1 if *Slack* is less than zero and zero otherwise.	Compustat, DealScan
Fee	Fee, in basis points, disclosed in borrower 8-K filings.	SEC Form 8-K
Switch	Indicator that equals 1 if the borrower selects a new lender on its subsequent loan and zero otherwise.	
ΔECD	The one-year ahead change in the expected cost of default, where the expected cost of default is based on the timing and incidence of subsequent "D" credit ratings, whether or not the loan is secured, and present values of losses based on LIBOR plus the loan spread. See Section 3.2.3 for details.	Compustat, DealScan, FRED
Return on equity	The ratio of net income to book equity.	Compustat
Loan loss reserves	The ratio of loan loss reserves to total assets.	Compustat
Equity capital ratio	The ratio of book equity to total assets.	Compustat
High discretionary acc.	Indicator that equals 1 if the borrower exceeds the median level of discretionary accruals as in Teoh, Welch, and Wong (1998).	Compustat
High goodwill	Indicator that equals 1 if the borrower exceeds the median ratio of goodwill to total assets.	Compustat
High intangibility	Indicator that equals 1 if the borrower has less than the median ratio of tangible assets to total assets.	Compustat
High loan-to-assets	Indicator that equals 1 if the loan exceeds	Compustat,

	the median ratio of loan amount to total assets.	DealScan
High rating	Indicator that equals 1 if the borrower exceeds the median credit rating.	Compustat
Competitive	Indicator that equals 1 if more than the median number of other banks have outstanding loans to borrowers in the same two-digit SIC and state.	DealScan
Multiple banks	Indicator that equals 1 if the borrower has outstanding loans from multiple lead banks.	DealScan
Strong relationship	Indicator that equals 1 if the length of the lead bank-borrower relationship exceeds the median number of years.	DealScan
Cross-selling	Indicator that equals 1 if the borrower has outstanding loans with multiple types and tranches.	DealScan
M/B	The ratio of market capitalization divided by book equity.	Compustat
Leverage	The ratio of the sum of debt in current liabilities and long-term debt to total assets.	Compustat
Market capitalization	The product of fiscal period closing price and common shares outstanding.	Compustat

Table A2. Covenant Calculations

Covenant Name	Calculation (Compustat codes)
Debt/EBITDA	(DLCQ + DLTTQ) / Rolling EBITDA
Debt/Equity	(DLCQ + DLTTQ) / SEQQ
Debt/Tang. NW	(DLCQ + DLTTQ) / (ATQ – INTANQ – LTQ)
Leverage	(DLCQ + DLTTQ) / ATQ
Current ratio	ACTQ/LCTQ
Quick ratio	(RECTQ + CHEQ) / LCTQ
Cash interest cov.	Rolling EBITDA/Rolling interest paid
Interest coverage	Rolling EBITDA/Rolling interest expense
Debt service cov.	Rolling EBITDA/(Rolling interest expense and principal payment)
Fixed charge cov.	Rolling EBITDA/(Rolling interest expense, principal payment, and rent payment)
Net worth	ATQ – LTQ
Tangible net worth	ATQ – INTANQ – LTQ
EBITDA	Rolling EBITDA

Rolling EBITDA*, interest expense, interest paid, principal paid* are the sum of the firm's past four quarters.

Appendix B. Alternative Specifications

Figure B1. Simulated Value of Relationship Estimates Relaxing Independence of Inputs

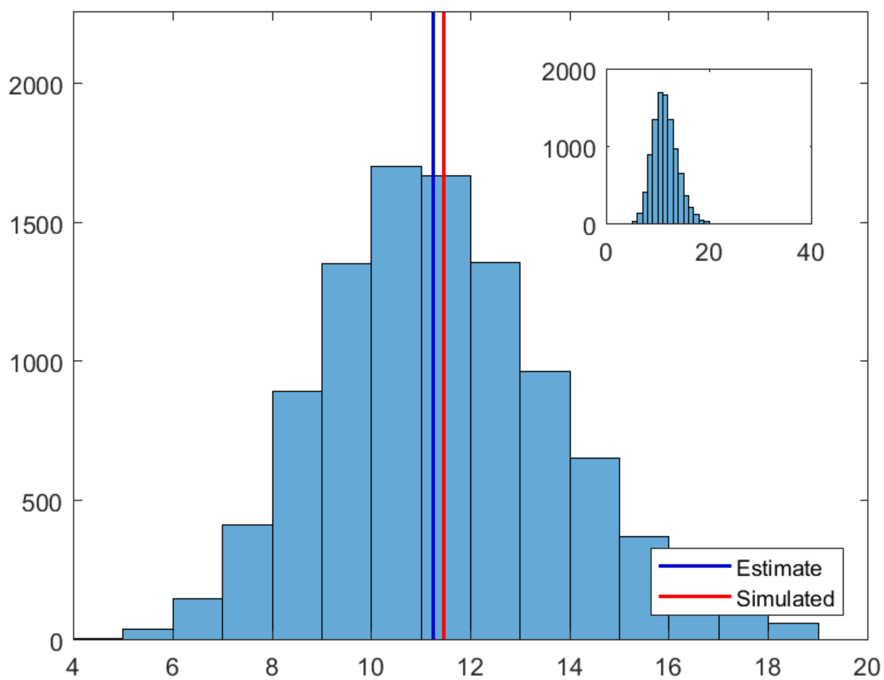

Table B1. First Stage Regression Discontinuity Estimates

This table presents regression discontinuity design estimates of *Enforcement*, an indicator that equals one if the borrower discloses a material covenant violation in an SEC filing and zero otherwise, on *Breach*, an indicator that equals one if the borrower is in breach of at least one covenant threshold and zero otherwise. The running variable is *Slack*, the minimum standardized distance to a pre-set covenant threshold across financial covenants in the loan package. Heteroskedasticity-robust standard errors are clustered by lender, and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels. Local polynomial control functions are estimated using an Epanechnikov kernel. The specification uses optimal bin sizes. In Panel A, the specification selects optimal bandwidths using the MSE-optimal criterion. Optimal bandwidths and the implied effective number of observations are reported for each specification.

	Enforcement			
	(1)	(2)	(3)	(4)
Breach	0.151***	0.144***	0.144***	0.142***
	(0.016)	(0.018)	(0.018)	(0.019)
Poly. order	0	1	2	3
Optimal BW	1.055	4.145	11.196	17.471
Kernel	*Epanech.*	*Epanech.*	*Epanech.*	*Epanech.*
#Clusters	[44, 51]	[44, 51]	[44, 51]	[44, 51]
Effective Obs.	31,013	48,378	56,648	58,476

Table B2. Fuzzy Regression Discontinuity Estimates

This table presents fuzzy regression discontinuity design estimates of *Switch*, an indicator that equals one if the borrower switches to a new lead bank on its next loan and zero otherwise, and ΔECD, the forward-looking change in the expected cost of default, on *Enforcement*, an indicator that equals one if the borrower discloses a material covenant violation in an SEC filing and zero otherwise. Panel A presents estimates for *Switch*, and Panel B presents estimates for ΔECD. *Enforcement* is instrumented using the covenant breach cutoff in the running variable *Slack*, the minimum standardized distance to a pre-set covenant threshold across financial covenants in the loan package. Heteroskedasticity-robust standard errors are clustered by lender, and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels. Panel A presents estimates using the optimal specification in which bandwidths are selected using MSE-optimal criterion and the local polynomial control functions are estimated using Epanechnikov kernels (Calonico, Cattaneo, and Titiunik 2014).

Panel A. *Switch*

	(1)	(2)	(3)	(4)
$\widehat{Enforcement}$	0.324**	0.322**	0.311**	0.331**
	(0.132)	(0.144)	(0.145)	(0.143)
Poly. order	0	1	2	3
Optimal BW	0.982	4.833	13.282	21.659
Kernel	*Epanech.*	*Epanech.*	*Epanech.*	*Epanech.*
#Clusters	[44, 51]	[44, 51]	[44, 51]	[44, 51]
Effective Obs.	30,046	49,892	57,560	58,889

Panel B. ΔECD

	(1)	(2)	(3)	(4)
$\widehat{Enforcement}$	-3.442***	-3.001***	-3.064***	-3.155***
	(0.653)	(0.659)	(0.702)	(0.739)
Poly. order	0	1	2	3
Optimal BW	1.879	6.111	11.433	20.169
Kernel	*Epanech.*	*Epanech.*	*Epanech.*	*Epanech.*
#Clusters	[40, 40]	[40, 40]	[40, 40]	[40, 40]
Effective Obs.	27,885	36,839	40,042	41,327

Appendix C. Investigating Input Correlations

In our preferred specification, column (5) of Table 5, we control for biases that nonlinearity of equation (12) and lack of independence across errors in our estimating equations may have on our estimate of the value of relationships. We do this by using a bootstrapping procedure across our estimates to calculate within-sample draw values for *VOR*, averaging across them, as well as to generate standard errors. This adjustment produces an estimate of 11.566%, with a standard error of 2.546.

Rather than simply rely on the non-parametric bootstrapping procedure, in this Appendix, we also explore a parametric correction for our nonlinear transformation and assumptions of independence. Namely, we take our estimates from columns (1), (2), and (3) of Table 5 for ϕ, or *Fee*, ω, or change in the expected cost of default, ψ, or the increase in switching rates as well as the standard errors. We also estimate the correlation in these estimates within bootstrapped samples in Table C1, finding that ω and ψ are statistically significantly correlated, but correlations across these values are all economically small. Nevertheless, we use these estimated correlations in our simulations.

We perform 10,000 simulations of a multivariate normal distribution for each of these outcomes, with means and standard errors from Table 5 and cross-correlations as in Table C1. In each draw, we calculate *VOR*, or the value of relationships, using equation (16). This procedure therefore corrects for bias due to nonlinearity in variables of equation (16) and corrects for any violation of our independence assumption using the correlations in estimates. Once we have completed these simulations, we find that the mean of *VOR* is 11.494, with a standard deviation of 2.523, each of these estimates quantitatively similar to our nonparametric bootstrapping correction as in column (5) of Table 5. The consistency across these approaches lends support to both our approach and the robustness of our findings.

Table C1. Independence of Unobservables

This table presents correlations between parameter estimates in the baseline estimation of the *Value of Relationships* system of simultaneous equations from Table 5. Correlations are calculated from parameter estimates of the sample of 10,000 repeated bootstrapped subsamples. p-values are presented in parentheses, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

	$\rho_{e,s}$	$\rho_{e,f}$	$\rho_{s,f}$
	(1)	(2)	(3)
Correlation	-0.017*	0.005	0.004
	(0.086)	(0.631)	(0.716)

Figure 1. Distribution of Waiver and Amendment Fees

This figure presents a density plot of the distribution of covenant waiver and loan amendment fees. Fee data come from 8-K filings.

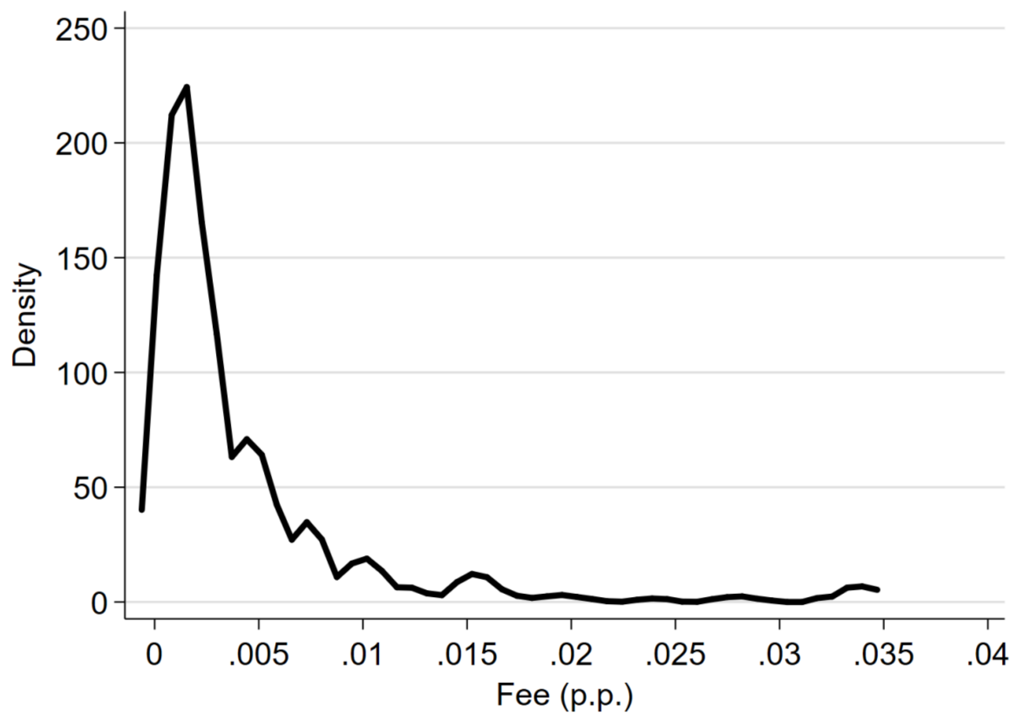

Figure 2. Enforcement Rates Around the Covenant Breach Cutoff (*First Stage*)

This figure presents a regression discontinuity plot of the probability of enforcement on *Slack*, the minimum standardized distance to pre-set covenant thresholds within a covenant package, around the covenant breach cutoff. Quadratic polynomial control functions and associated 95% confidence intervals are estimated and presented with solid and dashed black lines, respectively, on each side of the cutoff, which is highlighted by the dashed red vertical line. The hollow navy scatter plot shows conditional means of enforcement propensity within bins of *Slack*. The bandwidth is three standard deviations of the underlying covenant measure.

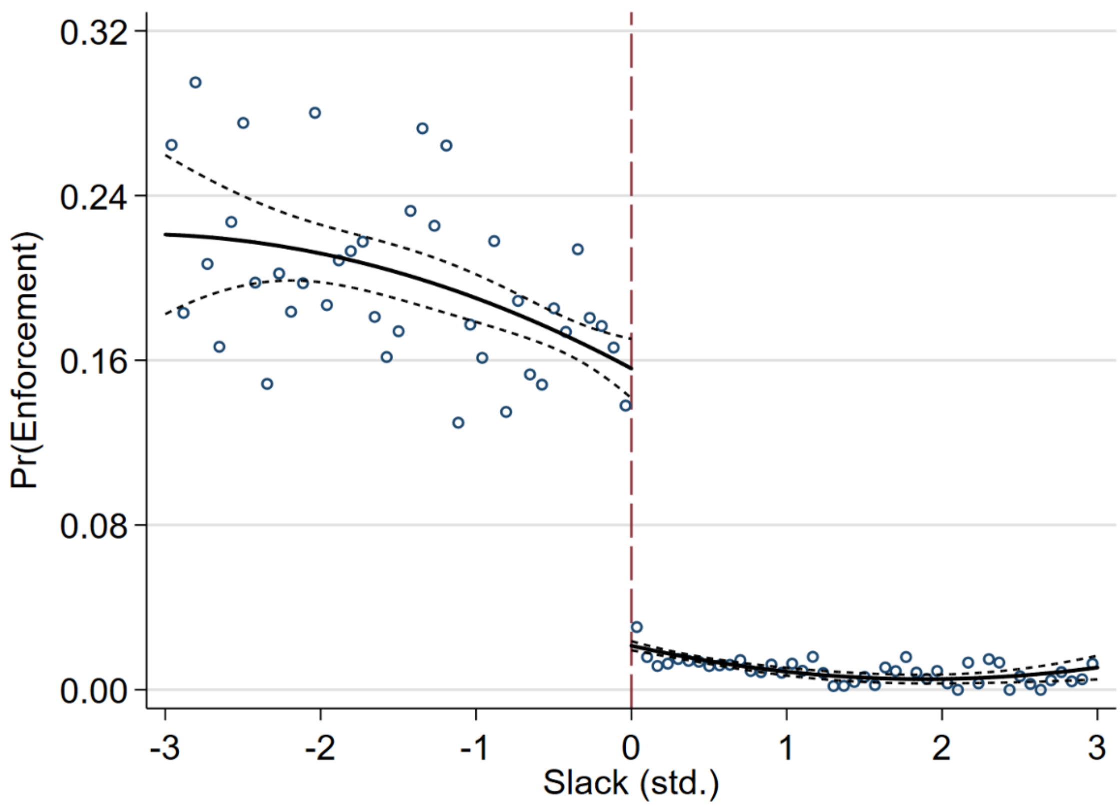

Figure 3. Expected Default Costs Around the Breach Cutoff (*Reduced Form*)

This figure presents a regression discontinuity plot of the one-year change in the expected cost of default on *Slack*, the minimum standardized distance to pre-set covenant thresholds within a covenant package, around the covenant breach cutoff. Quadratic polynomial control functions and associated 95% confidence intervals are estimated and presented with solid and dashed black lines, respectively, on each side of the cutoff, which is highlighted by the dashed red vertical line. The hollow navy scatter plot shows conditional means of enforcement propensity within bins of *Slack*. The bandwidth is three standard deviations of the underlying covenant measure.

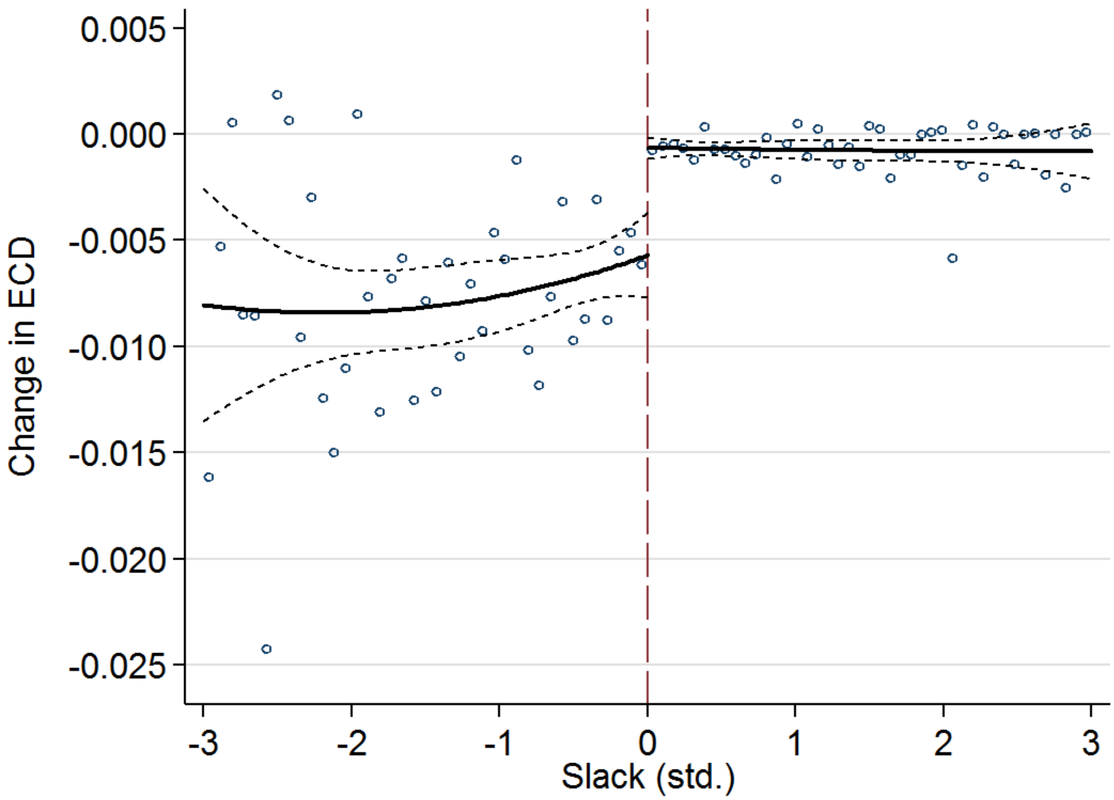

Figure 4. Lender Switching Rates Around the Covenant Breach Cutoff (*Reduced Form*)

This figure presents a regression discontinuity plot of the probability of switching lenders on *Slack*, the minimum standardized distance to pre-set covenant thresholds within a covenant package, around the covenant breach cutoff. Quadratic polynomial control functions and associated 95% confidence intervals are estimated and presented with solid and dashed black lines, respectively, on each side of the cutoff, which is highlighted by the dashed red vertical line. The hollow navy scatter plot shows conditional means of enforcement propensity within bins of *Slack*. The bandwidth is three standard deviations of the underlying covenant measure.

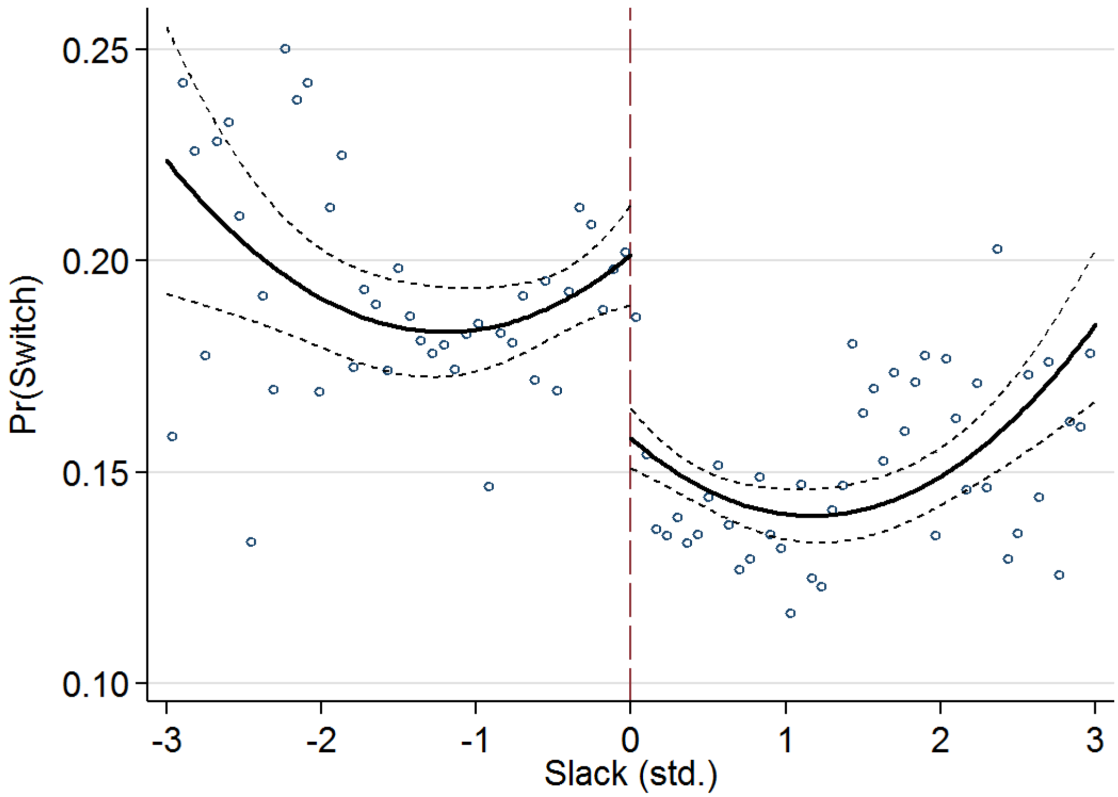

Figure 5. Local Continuity in Borrower Characteristics

This figure presents regression discontinuity plots of borrower characteristics at loan initiation on *Slack*, the minimum standardized distance to pre-set covenant thresholds within a covenant package, around the covenant breach cutoff. Local polynomial control functions and associated 95% confidence intervals are estimated and presented with solid and dashed black lines, respectively, on each side of the cutoff, which is highlighted by the dashed red vertical line. The bandwidth is three standard deviations of the underlying covenant measure. Panels (a)-(d) present evidence of smoothness in relationship value, initial *Slack*, M/B, and market capitalization. Panels (e)-(p) present evidence of smoothness in 12 measures commonly contracted upon in financial covenants.

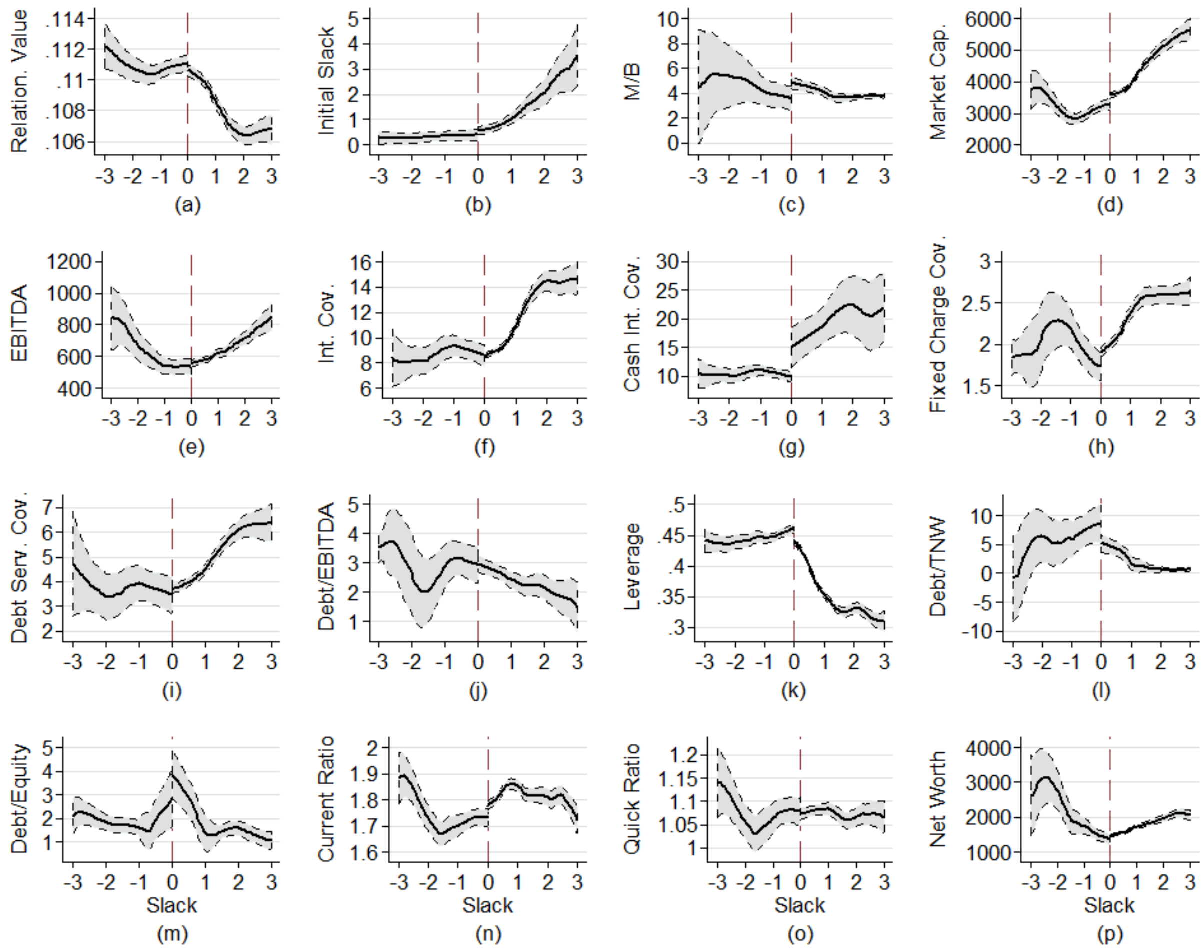

Figure 6. External Validity

This figure presents estimates of conditional means and 95% confidence intervals of the probability that a loan ever breaches a covenant threshold before maturity based on quintiles of borrower characteristics at loan initiation. The specification removes unobserved borrower heterogeneity and secular trends by calendar-quarter. The first quintile contains the lowest values of the underlying measure, and the fifth quintile contains the highest values. Conditional means are plotted with solid black lines, and their associated 95% confidence intervals are represented by the shaded gray areas and dashed black lines. Panels (a)-(d) present evidence of the probability of a breach conditional on relationship value, initial *Slack*, M/B, and market capitalization. Panels (e)-(p) present evidence of the probability of a breach conditional on 12 measures commonly contracted upon in financial covenants. The absence of an upward or downward trend in conditional means across quintiles suggests a lack of predictability of covenant breaches at loan initiation.

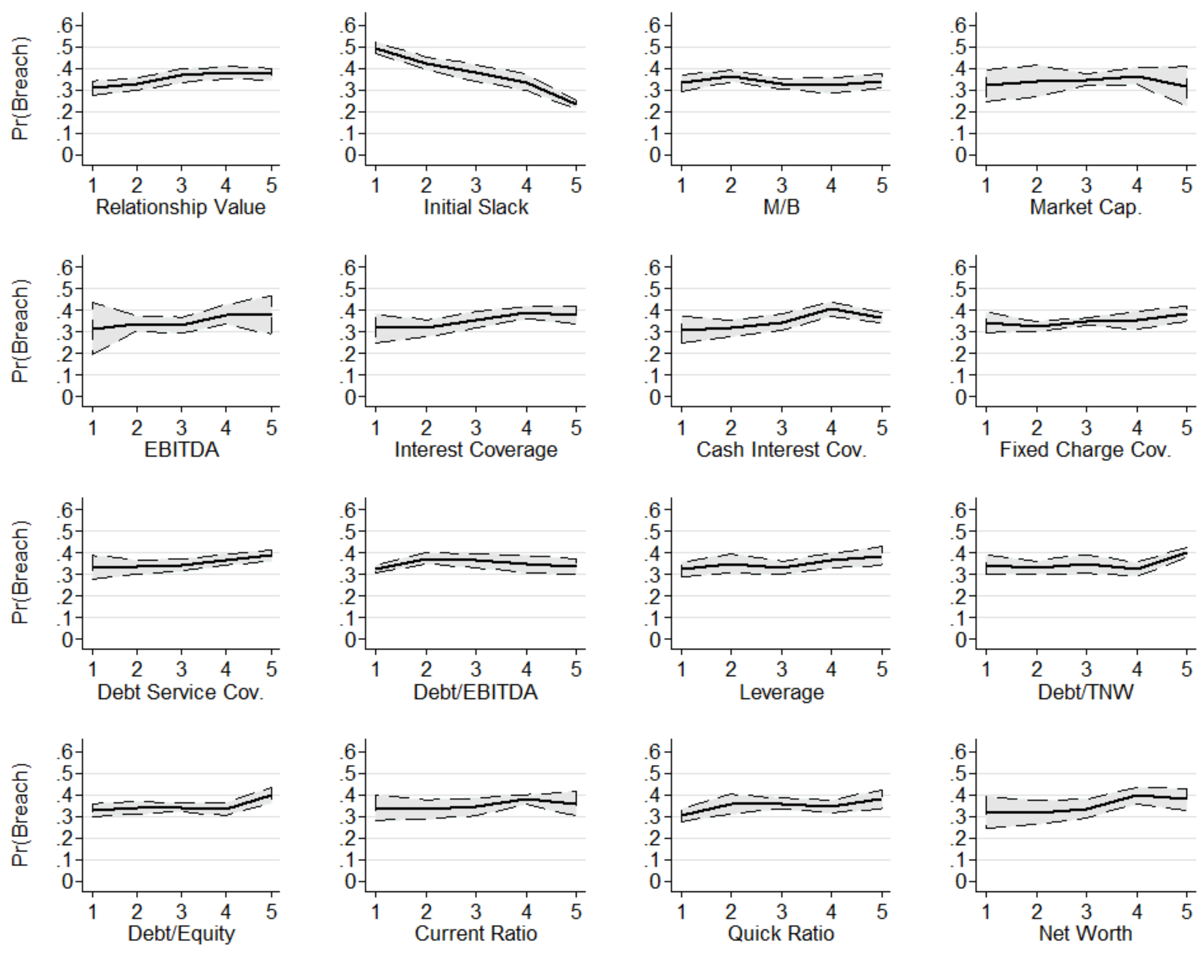

Figure 7. Bank-level Relationship Capital

This figure presents a histogram of relationship capital divided by total assets in a bank-year panel. The average bank has relationship capital equivalent to 6.6% of total assets, though the 10th percentile is 3.6% and the 90th percentile is 9.2%.

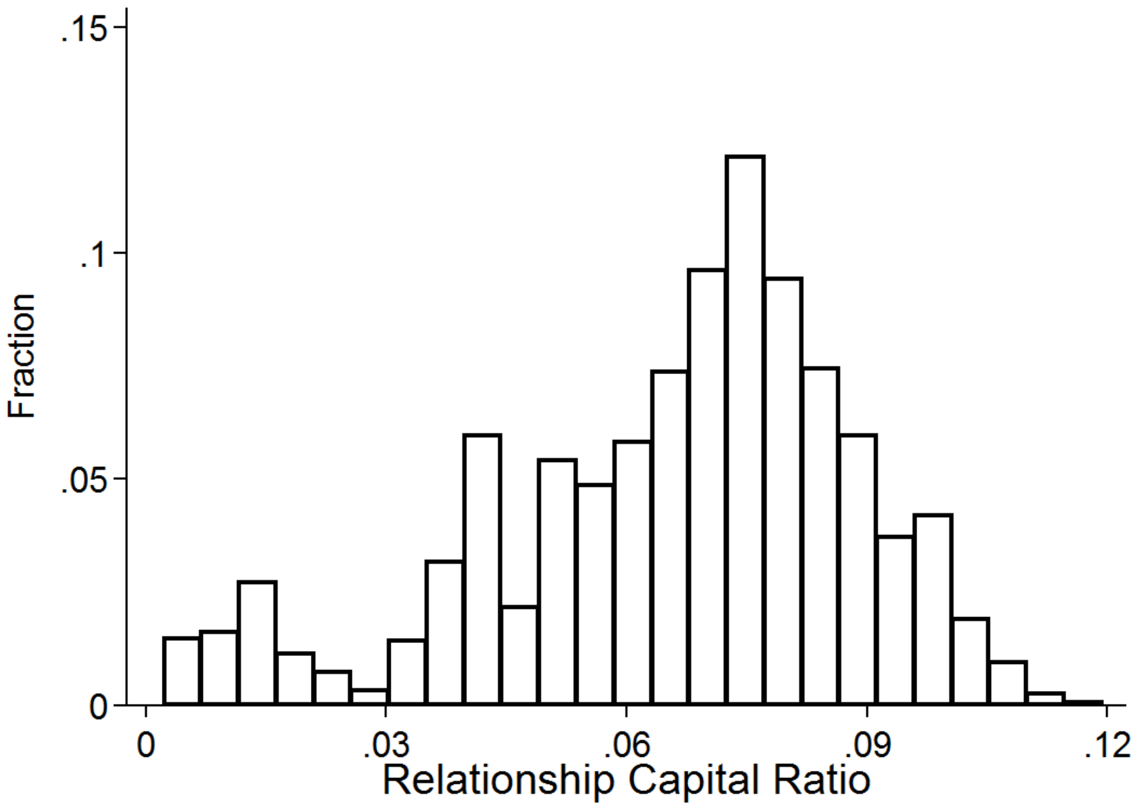

Figure 8. Relationship Capital and Bank Characteristics

This figure presents bin scatter plots of the relationship between bank characteristics and relationship capital intensity in a bank-year panel. We define relationship capital intensity as the ratio of relationship capital to the sum of relationship capital and equity capital. Subfigure (a) presents evidence of the negative relationship between bank size and relationship capital intensity. Subfigure (b) presents evidence of the negative relationship between the bank's reliance on short-term debt as a fraction of total debt and relationship capital intensity. Subfigure (c) presents evidence of the positive relationship between profitability, which we measure using return on equity, and relationship capital intensity. Subfigure (d) presents evidence of the negative relationship between loan loss reserves, which we define as the fraction of loan loss reserves to total assets, and relationship capital intensity. All variables are transformed into percentiles within calendar-quarter for ease of presentation.

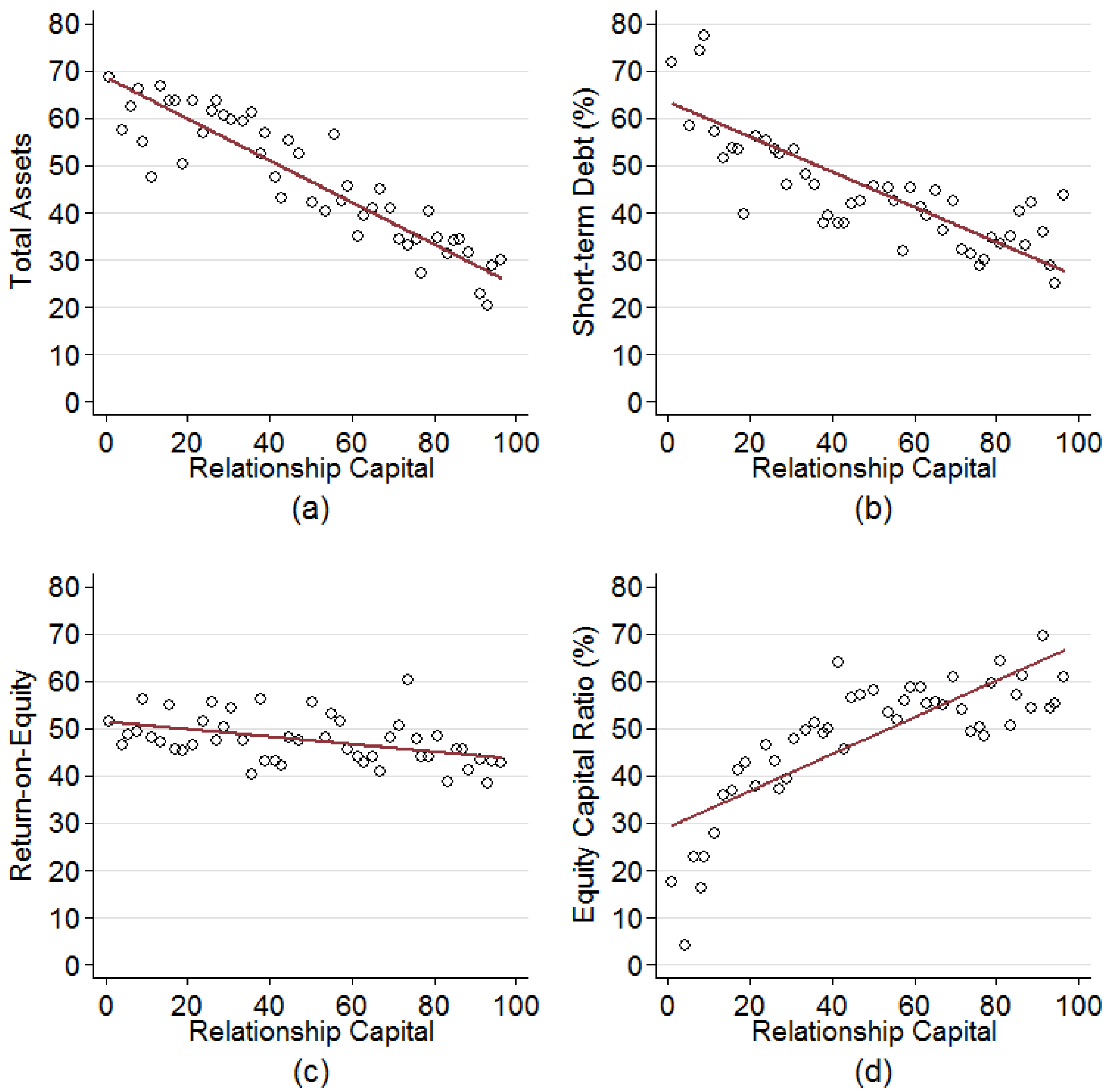

Figure 9. Bank Capital over Time

This figure presents the mean and 95% confidence interval for two different capital ratios during our sample period. Subfigure (a) presents the time series pattern of the ratio of equity capital to total assets, and subfigure (b) presents the time series pattern of the ratio of relationship capital to total assets.

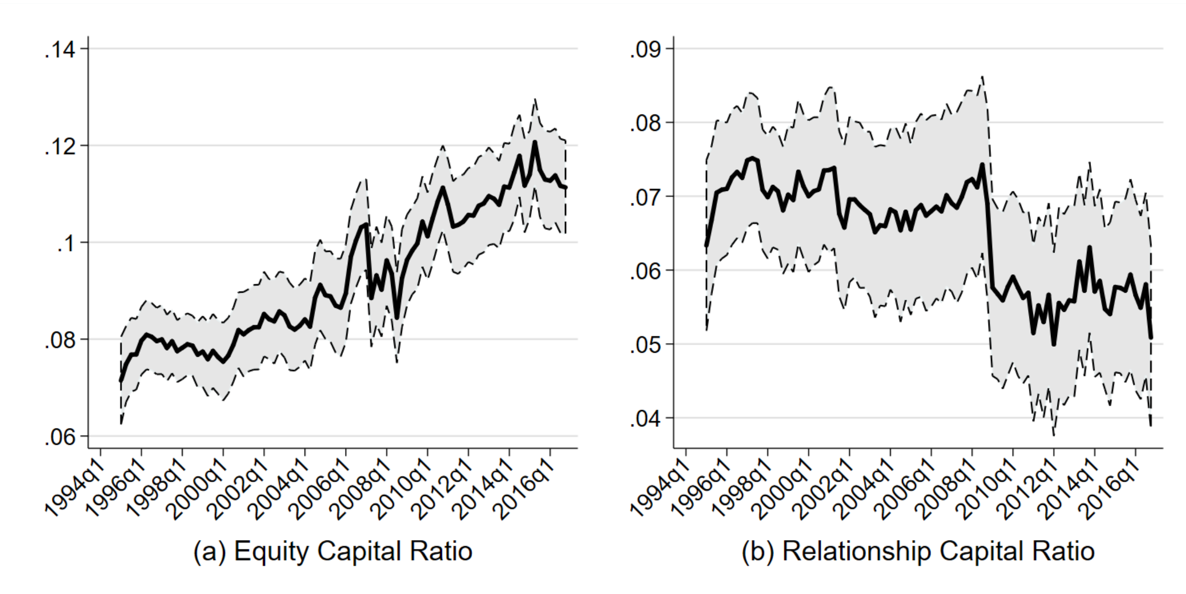

Figure 10. Relationship Capital and Bank Value

This figure presents bins catter plots of the relationship between bank value and relationship capital intensity in a bank-year panel. We measure bank value using M/B, the ratio of market capitalization to book equity, and define relationship capital intensity as the ratio of relationship capital to the sum of relationship capital and equity capital. Subfigure (a) presents evidence of the positive relationship between M/B and relationship capital intensity in levels, and subfigure (b) presents evidence of the positive relationship between M/B and and relationship capital intensity in first differences. All variables are transformed into percentiles within calendar-quarter for ease of presentation.

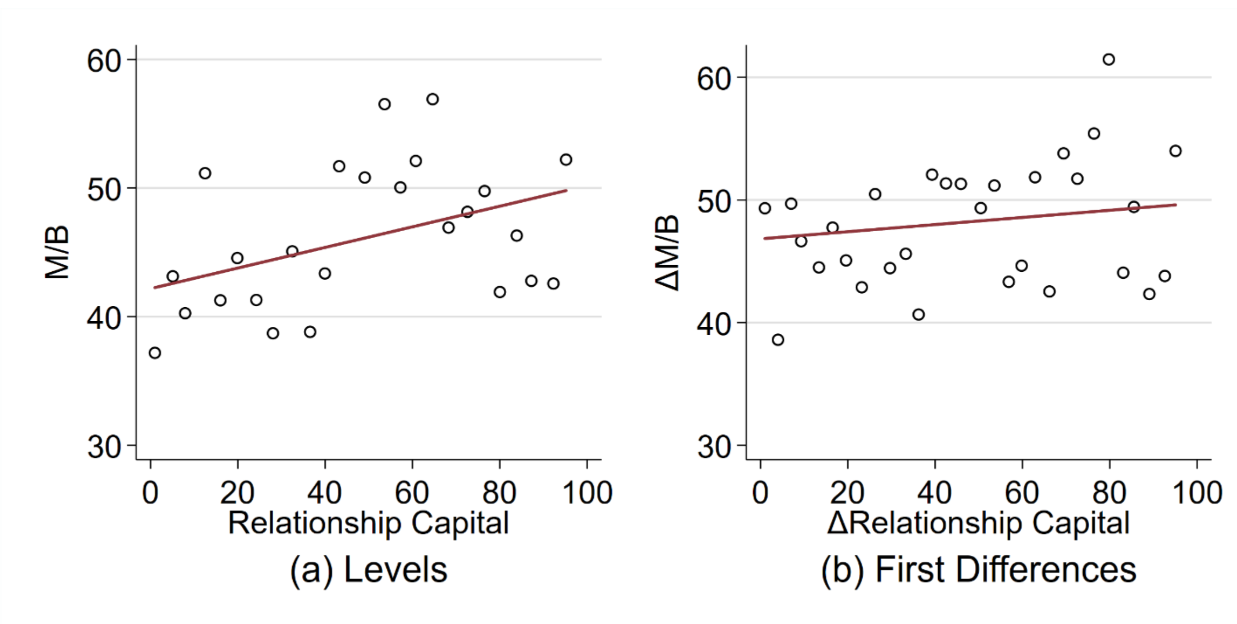

Table 1. Summary Statistics

This table presents summary statistics for the key variables in our analysis. The sample is restricted to a 10σ bandwidth around the covenant threshold.

	Mean	SD	P25	Median	P75
Switch	15.37%				
ΔECD	-0.23%	3.30%			
$\Delta Pr(Default^{3yr})$	-0.64%	9.80%			
Fee	0.45%	0.90%	0.10%	0.25%	0.50%
Enforcement	5.18%				
Breach	20.99%				
Slack	1.07	2.52	0.03	0.45	1.78
Spread (bps)	170.97	115.05	75	150	239
Amount ($mm)	841.67	1,144.51	264	500	1,000
Maturity (mos.)	58.31	13.34	50	60	61
Secured	55.19%				

Table 2. First Stage Estimates of Enforcement Rates

This table presents regression discontinuity design estimates of *Enforcement*, an indicator that equals one if the borrower discloses a material covenant violation in an SEC filing and zero otherwise, on *Breach*, an indicator that equals one if the borrower is in breach of at least one covenant threshold and zero otherwise. The running variable is *Slack*, the minimum standardized distance to a pre-set covenant threshold across financial covenants in the loan package. Column (1) presents evidence using a bandwidth of one unit of *Slack* (i.e., one standard deviation of the underlying covenant measure from the breach threshold) and no polynomial control functions. Column (2) presents evidence using a bandwidth of five units of *Slack* and linear polynomial control functions. Column (3) presents evidence using a bandwidth of ten units of *Slack* and quadratic polynomial control functions. Column (4) presents evidence using a bandwidth of twenty units of *Slack* and cubic polynomial control functions. Heteroskedasticity-robust standard errors are clustered by lender, and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels. Appendix B contains evidence of robustness to alternative specifications that vary parameters of the regression discontinuity estimator.

Dependent variable: *Enforcement*				
	(1)	(2)	(3)	(4)
Breach	0.153***	0.149***	0.144***	0.146***
	(0.014)	(0.015)	(0.015)	(0.016)
Polynomial order	0	1	2	3
Bandwidth	1	5	10	20
Adj. R^2	0.0850	0.1098	0.1150	0.1186
Obs.	30,301	50,232	55,983	58,761

Table 3. Fuzzy RDD Estimates of Change in Expected Cost of Default

This table presents fuzzy regression discontinuity design estimates of ΔECD, the forward-looking change in the expected cost of default, on *Enforcement*, an indicator that equals one if the borrower discloses a material covenant violation in an SEC filing and zero otherwise. *Enforcement* is instrumented using the covenant breach cutoff in the running variable *Slack*, the minimum standardized distance to a pre-set covenant threshold across financial covenants in the loan package. Column (1) presents evidence using a bandwidth of one unit of *Slack* (i.e., one standard deviation of the underlying covenant measure from the breach threshold) and no polynomial control functions. Column (2) presents evidence using a bandwidth of five units of *Slack* and linear polynomial control functions. Column (3) presents evidence using a bandwidth of ten units of *Slack* and quadratic polynomial control functions. Column (4) presents evidence using a bandwidth of twenty units of *Slack* and cubic polynomial control functions. Heteroskedasticity-robust standard errors are clustered by lender, and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels. Associated first stage regression discontinuity estimates of enforcement propensities are presented in Table 2. First stage *F*-statistics exceed critical values in all specifications. Appendix B contains evidence of robustness to alternative specifications that vary parameters of the fuzzy regression discontinuity estimator.

Dependent variable: ΔECD				
	(1)	(2)	(3)	(4)
$\widehat{Enforcement}$	-3.524***	-2.901***	-2.860***	-2.750***
	(0.740)	(0.690)	(0.734)	(0.706)
Polynomial order	0	1	2	3
Bandwidth	1	5	10	20
Obs.	21,712	35,651	39,492	41,318

Table 4. Fuzzy RDD Estimates of Lender Switching Rates

This table presents fuzzy regression discontinuity design estimates of *Switch*, an indicator that equals one if the borrower switches to a new lead bank on its next loan and zero otherwise, on *Enforcement*, an indicator that equals one if the borrower discloses a material covenant violation in an SEC filing and zero otherwise. *Enforcement* is instrumented using the covenant breach cutoff in the running variable *Slack*, the minimum standardized distance to a pre-set covenant threshold across financial covenants in the loan package. Column (1) presents evidence using a bandwidth of one unit of *Slack* (i.e., one standard deviation of the underlying covenant measure from the breach threshold) and no polynomial control functions. Column (2) presents evidence using a bandwidth of five units of *Slack* and linear polynomial control functions. Column (3) presents evidence using a bandwidth of fifteen units of *Slack* and quadratic polynomial control functions. Column (4) presents evidence using a bandwidth of twenty-five units of *Slack* and cubic polynomial control functions. Heteroskedasticity-robust standard errors are clustered by lender, and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels. Associated first stage regression discontinuity estimates of enforcement propensities are presented in Table 2. First stage *F*-statistics exceed critical values in all specifications. Appendix B contains evidence of robustness to alternative specifications that vary parameters of the fuzzy regression discontinuity estimator.

Dependent variable: *Switch*				
	(1)	(2)	(3)	(4)
$\widehat{Enforcement}$	0.312***	0.296***	0.290***	0.303***
	(0.095)	(0.103)	(0.102)	(0.103)
Polynomial order	0	1	2	3
Bandwidth	1	5	15	25
Obs.	30,301	50,232	58,040	59,055

Table 5. Value of Lending Relationships: Parameter Estimates

This table presents baseline estimates of the value of lending relationships. The *Fee* parameter estimate presented in column (1) is the average waiver or amendment fee paid by the borrower. Parameters corresponding to the expected cost of default (ΔECD) and switching (*Switch*) responses in columns (2) and (3) are estimated using the baseline fuzzy regression discontinuity design with linear polynomials in a narrow bandwidth around the covenant breach threshold as presented in column (2) of Tables 3 and 4. Based on the model and corresponding system of equations developed in Section 3, we estimate the parameters presented in columns (1)-(3) and a nonlinear function of those parameters, the *Value of Relationships*. We estimate the system of simultaneous equations using a non-parametric bootstrapping approach with 10,000 repetitions, which addresses both functional form and a unobserved heterogeneity in borrower responses that could lead to correlations among parameter estimates in columns (1)-(3). The estimate of the *Value of Relationships* in column (4) corresponds to the bootstrapped estimate of the nonlinear function, and its standard error is calculated assuming independence in borrower response parameters. In column (5), we present an estimate of the *Value of Relationships* that relaxes the assumption of independence in borrower responses. This estimate is the average *Value of Relationships* parameter across bootstrapped samples, and the corresponding standard error is the bootstrapped standard error. Heteroskedasticity-robust standard errors are clustered by lender, and presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

Parameter	ϕ	ω	ψ	*VOR*	
				$\perp$	$\perp$-adj.
	(1)	(2)	(3)	(4)	(5)
Estimate	0.447***	-2.901***	0.296***	11.309***	11.566***
S.E.	(0.029)	(0.558)	(0.040)	(2.536)	(2.546)

Table 6. Value of Lending Relationships: Robustness

This table contrasts baseline estimates of the *Value of Relationships* with estimates from robustness tests that explore functional form, the role of covenant manipulation, observed borrower heterogeneity, and unobserved heterogeneity. Row (1) presents the baseline estimates as in Table 5. Columns (2) and (3) present estimates with quadratic and cubic polynomials, respectively, in the equations that generate parameters presented in columns (1) and (2). Columns (4)-(6) present estimates with local linear, quadratic, and cubic polynomials using Epanechnikov kernel estimators, respectively, in the equations that generate the parameters presented in columns (1) and (2). In rows (7)-(9), we present estimates using linear, quadratic, and cubic polynomials, respectively, using an alternative definition of covenant slack based only on covenant types for which McCrary (2008) tests reveal no evidence of manipulation. In row (10) we impute waiver and amendment fees based on a flexible cubic polynomial function of breach severity. In row (11), we restrict the sample to loan-quarter observations for which we observe both switching and changes in the expected cost of default. In rows (12)-(13), we present estimates from samples that exclude the last or first two years of the sample period, respectively. In rows (14)-(18), we present estimates that control for borrower characteristics (e.g., M/B, market capitalization, and the initial values of the underlying covenant variables defined in Table A2 in Appendix A), industry fixed effects, calendar-quarter fixed effects, lender fixed effects, and borrower fixed effects, respectively. Estimates in all rows are derived from a bootstrapped system of simultaneous equations with 10,000 repetitions. Column (4) estimates of the *Value of Relationships* allow for correlation in borrower responses (as in column (5) of Table 5). ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

		ϕ	ω	ψ	VOR
		(1)	(2)	(3)	(4)
(1)	**Baseline**	0.435***	-2.901***	0.296***	11.566***
		(0.028)	(0.562)	(0.040)	(2.546)
	Robustness				
	Functional form				
(2)	*Quadratic*	0.435***	-2.860***	0.290***	11.665***
		(0.029)	(0.633)	(0.041)	(2.749)
(3)	*Cubic*	0.435***	-2.750***	0.303***	10.784***
		(0.028)	(0.634)	(0.045)	(2.630)
(4)	*Local linear*	0.435***	-3.000***	0.322***	11.261***
		(0.016)	(0.571)	(0.045)	(2.403)
(5)	*Local quadratic*	0.435***	-3.064***	0.311***	11.318***
		(0.016)	(0.666)	(0.048)	(2.646)
(6)	*Local cubic*	0.435***	-3.155***	0.331***	11.281***
		(0.016)	(0.736)	(0.050)	(2.725)
	No Manipulation				
(7)	$Linear^{NoManip.}$	0.447***	-3.263***	0.291***	13.111***
		(0.034)	(0.393)	(0.028)	(2.103)
(8)	$Quadratic^{NoManip}$	0.447***	-3.310***	0.302***	12.715***
		(0.050)	(0.464)	(0.031)	(2.015)
(9)	$Cubic^{NoManip}$	0.447***	-3.212***	0.314***	12.063***
		(0.050)	(0.465)	(0.031)	(1.925)

	Sample selection				
(10)	*Fee imputation*	0.407***	-2.901***	0.296***	11.453***
		(0.0002)	(0.558)	(0.040)	(2.534)
(11)	*Constant sample*	0.446***	-2.901***	0.257***	13.431***
		(0.031)	(0.559)	(0.044)	(3.344)
(12)	*Restrict late*	0.449***	-2.984***	0.273***	12.898***
		(0.029)	(0.587)	(0.042)	(3.041)
(13)	*Restrict early*	0.450***	-3.074***	0.280***	12.881***
		(0.029)	(0.577)	(0.041)	(2.839)
	Heterogeneity:				
(14)	*Observables*	0.447***	-2.382***	0.333***	8.845***
		(0.039)	(0.641)	(0.052)	(2.449)
(15)	*Industry*	0.447***	-3.080***	0.298***	12.094***
		(0.027)	(0.572)	(0.039)	(2.584)
(16)	*Calendar-quarter*	0.447***	-2.821 ***	0.194***	17.821***
		(0.027)	(0.583)	(0.040)	(5.572)
(17)	*Lender*	0.447***	-2.962***	0.245***	14.334***
		(0.026)	(0.586)	(0.041)	(3.491)
(18)	*Borrower*	0.447***	-3.030***	0.241***	14.735***
		(0.028)	(0.654)	(0.045)	(4.395)

Table 7. Value of Lending Relationships: The Role of Opacity

This table presents estimates of the *Value of Relationships* in subsamples of borrowers with high and low opacity. Rows (1) and (2) present estimates from subsamples of borrowers with low and high discretionary accruals, respectively. Discretionary accruals is defined using the model of Teoh, Welch, and Wong (1998). Rows (3) and (4) present estimates from subsamples of borrowers with low and high analyst forecast dispersion, respectively. Borrowers with high dispersion have above the median analyst forecast dispersion. Rows (5) and (6) present estimates from subsamples of borrowers with low and high goodwill balances, respectively. Borrowers with high goodwill have above the median ratio of goodwill to total assets. Rows (7) and (8) present estimates from subsamples of borrowers with low and high intangibility, respectively. Borrowers with high intangibility have below median ratios of tangible assets to total assets. Estimates in all rows are derived from a bootstrapped system of simultaneous equations with 10,000 repetitions. For each set of cross-sectional tests, we present the *p-value* from a binomial test of the proportion of replicant samples in which the parameter estimates are different. Column (4) estimates of the *Value of Relationships* allow for correlation in borrower responses (as in column (5) of Table 5). ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

		ϕ	ω	ψ	*VOR*
		(1)	(2)	(3)	(4)
(1)	*Low discretionary acc.*	0.350***	-4.209***	0.502***	9.210***
		(0.016)	(1.421)	(0.061)	(2.281)
(2)	*High discretionary acc.*	0.539***	-1.905**	0.153***	18.633
		(0.045)	(0.829)	(0.047)	(12.328)
	p-value	<0.001	<0.001	<0.001	<0.001
(3)	*Low dispersion*	0.428***	-1.745**	0.418***	5.302***
		(0.053)	(0.742)	(0.064)	(1.977)
(4)	*High dispersion*	0.460***	-3.652***	0.182***	25.254**
		(0.032)	(0.818)	(0.052)	(12.881)
	p-value	<0.001	<0.001	<0.001	<0.001
(5)	*Low goodwill*	0.413***	-2.393***	0.288***	10.102***
		(0.037)	(0.856)	(0.034)	(3.199)
(6)	*High goodwill*	0.497***	-3.537***	0.206***	24.053
		(0.037)	(1.081)	(0.065)	(19.947)
	p-value	<0.001	<0.001	<0.001	<0.001
(7)	*Low intangibility*	0.462***	-2.550***	0.353***	8.692***
		(0.017)	(0.588)	(0.028)	(2.251)
(8)	*High intangibility*	0.426***	-3.615***	0.208**	23.212
		(0.065)	(1.170)	(0.066)	(18.050)
	p-value	0.536	<0.001	<0.001	<0.001

Table 8. Value of Lending Relationships: The Role of Lender Hold Up

This table presents estimates of the *Value of Relationships* in subsamples of borrowers with high and low opacity. Rows (1) and (2) present estimates from subsamples of borrowers with low and high loan-to-assets ratios, respectively. Rows (3) and (4) present estimates from subsamples of borrowers with low and high credit ratings, respectively. Rows (5) and (6) present estimates from subsamples of borrowers with low and high levels of competition in local banking markets, respectively. Rows (7) and (8) present estimates from subsamples of borrowers with and without outstanding loans from multiple lead banks, respectively. Rows (9) and (10) present estimates from subsamples of borrowers with weak and strong lending relationships with their lead banks, respectively. Rows (11) and (12) present estimates from subsamples of borrowers with and without cross-selling potential. Variable definitions are presented in Table A1 of Appendix A. Estimates in all rows are derived from a bootstrapped system of simultaneous equations with 10,000 repetitions. For each set of cross-sectional tests, we present the *p-value* from a binomial test of the proportion of replicant samples in which the parameter estimates are different. Column (4) estimates of the *Value of Relationships* allow for correlation in borrower responses (as in column (5) of Table 5). ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

		ϕ	ω	ψ	*VOR*
		(1)	(2)	(3)	(4)
(1)	*Low LTA*	0.536***	-2.780***	0.438***	7.856***
		(0.073)	(0.904)	(0.069)	(2.562)
(2)	*High LTA*	0.409***	-2.936***	0.214***	16.366***
		(0.025)	(0.771)	(0.043)	(5.523)
	p-value	<0.001	<0.001	<0.001	<0.001
(3)	*Low rating*	0.472***	-2.690***	0.184***	18.508***
		(0.036)	(0.866)	(0.049)	(7.000)
(4)	*High rating*	0.202***	-2.854*	0.856***	3.872**
		(0.015)	(1.476)	(0.117)	(1.724)
	p-value	<0.001	<0.001	<0.001	<0.001
(5)	*Low competition*	0.464***	-3.054***	0.291***	12.474***
		(0.048)	(0.496)	(0.046)	(3.045)
(6)	*High competition*	0.387***	-2.221**	0.306***	9.800
		(0.026)	(1.108)	(0.083)	(6.128)
	p-value	<0.001	<0.001	<0.001	<0.001
(7)	*Single bank*	0.441***	-2.681***	0.219***	14.867***
		(0.030)	(0.699)	(0.054)	(4.227)
(8)	*Multiple banks*	0.467***	-3.891***	0.780***	5.910**
		(0.075)	(1.376)	(0.080)	(2.386)
	p-value	<0.001	<0.001	<0.001	<0.001
(9)	*Weak relationship*	0.461***	-1.107	0.345***	6.400***
		(0.039)	(0.907)	(0.057)	(2.066)
(10)	*Strong relationship*	0.428***	-6.399***	0.208***	25.156*
		(0.033)	(1.473)	(0.063)	(13.556)
	p-value	<0.001	<0.001	<0.001	<0.001

(11)	*Cross-selling*	0.428***	-4.018***	0.269***	17.222***
		(0.022)	(0.516)	(0.029)	(4.700)
(12)	*No cross-selling*	0.472***	-1.717**	0.303***	7.763**
		(0.057)	(0.735)	(0.057)	(3.342)
	p-value	<0.001	<0.001	<0.001	<0.001

Table 9. Relationship Capital and Bank Value

This table presents regression estimates of *M/B*, the ratio of market capitalization to book equity, on *RelationshipCapital*, the ratio of relationship capital divided by total assets. See Section 5 for relationship capital calculations. Specifications incrementally include more restrictive fixed effects. Controls include the equity capital ratio and the natural log of total assets. Heteroskedasticity-robust standard errors are presented in parentheses. ***, **, and * denote results significant at the 1%, 5%, and 10% levels.

Dependent variable:	*M/B*			
	(1)	(2)	(3)	(4)
RelationshipCapital	11.150***	3.443**	9.835***	8.670***
	(2.212)	(1.591)	(3.248)	(3.230)
Controls	No	No	No	Yes
Fixed effects:				
Bank	No	No	Yes	Yes
Calendar-quarter	No	Yes	Yes	Yes
Adj. R^2	0.0274	0.2638	0.4420	0.4517
Obs.	1,442	1,442	1,438	1,438