Bank Monitoring of Borrowers and Borrowers' Investment Efficiency: Evidence from the Switch to the Expected Credit Loss Model

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Abstract

The recent switch from the incurred credit loss model to the expected credit loss model is an important change to bank financial reporting systems around the world. The expected credit loss model requires banks to monitor their borrowers closely for more timely recognition of loan losses. We posit and find that this close monitoring of potential loan losses enhances borrowers' investment-*q* sensitivity, consistent with such monitoring enhancing borrowers' investment efficiency. This effect is stronger for borrowers with greater bank dependence. It is also stronger in environments where banks themselves face more intense regulation and monitoring, indicating that the monitoring effects from regulation spill over to banks and then to borrowers. Overall, our study provides the novel insight that changes in the intensity of banks' monitoring of borrowers due to their financial reporting system can have real effects on their borrowers.

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1. Introduction

Banks have an important role as the delegated monitors of borrowers (Diamond 1984; Fama 1985), and bank accounting is vital to this monitoring process (Lim et al. 2014; Minnis and Sutherland 2017). In this paper, we use the switch from the incurred credit loss (ICL) model to the expected credit loss (ECL) model upon the adoption of International Financial Reporting Standard (IFRS) 9 Financial Instruments to study how the delegated monitoring required by bank financial reporting systems affect borrowers' investment efficiency.[1] Although prior studies investigate how various information-related features affect corporate decisions (see, e.g., the survey by Roychowdhury, Shroff, and Verdi 2019), to the best of our knowledge, no studies investigate how the financial reporting system of a firm's contracting party (specifically, banks) affects the investment efficiency of the firm itself.

The ECL model requires banks to closely monitor their borrowers to facilitate the timely recording of loan losses.[2] Anecdotal and limited empirical evidence suggests that adopting the ECL model could heighten the extent of bank monitoring of borrowers. For example, Deloitte (2016) indicates that banks need to monitor their loans to borrowers more intensely to properly identify the credit risk of loans. Specifically, Deloitte (2016, p. 44) notes that "the staging assessment uses all relevant information from processes used by the bank to measure and monitor credit risk. These processes require regular credit reviews or other monitoring and that all exposures are allocated to credit quality rating or risk grade based on the most recent review or other information."[3] Deloitte (2016) further highlights that under the

[1] The regulatory objective of the switch to the ECL model is to increase the timely recording of loan losses. The switch from the ICL model to the ECL model is widely regarded as the most momentous change in bank accounting in recent times (American Bankers Association 2016; Global Public Policy Committee 2016). The switch is also of practical relevance to banks because loan loss estimations based on the ECL model are material to the banks' financial statements (Deloitte 2016).
[2] Banks must closely monitor borrowers under the new regime in part because loan loss estimations based on the ECL model require detailed borrower information (e.g., historical experience of losses, delinquencies, and forward-looking macroeconomic factors) that could affect bank clients (Deloitte 2016).
[3] The survey conducted by Ernst & Young (2016) also notes that during the ECL regime, the role of the bank internal committees in managing credit risk will increase, especially once they decide to move a borrower to an internal "watch list."

ECL model, banks need to actively manage and monitor credit deterioration, including the use of qualitative indicators outlined in IFRS 9 to assess credit risk exposure. Deloitte (2016, pp. 45–46) notes that "if a bank intensifies the monitoring of a borrower or a class of borrowers and considers this is not indicative of a migration to stage 2, it should justify and document why a significant increase in credit risk has not occurred."[4] Moreover, recent research shows that the shift to the ECL regime leads to a reduction in borrowers' preference for bank debt relative to public bonds due to increased bank monitoring (Li, Ng, and Saffar 2022).

The switch to the ECL model provides a setting to study the effect of delegated monitoring required by bank financial reporting systems on borrowers' investment decisions. First, the literature shows that borrowers' investment losses contribute substantially to banks' loan losses (Dewenter and Hess 2003; Aristei and Gallo 2019). In many countries, beyond approving or rejecting loan applications, banks also provide loan syndication and advisory and networking services to facilitate borrowers' corporate investments (Moriarty, Kimball, and Gay 1983; Lincoln, Gerlach, and Ahmadjian 1996; Boot and Thakor 2000). Second, consistent with the ECL model's regulatory objective, evidence indicates that the ECL model leads to banks recognizing loan losses more timeously (Kim et al. 2021b; López-Espinosa, Ormazabal, and Sakasai 2021). To record loan losses timeously, banks must monitor borrowers closely. Thus, to the extent that closer monitoring reduces moral hazard that hinders the financing of investment opportunities and enhances relationship banking that facilitates the conversion of investment opportunities into investments, we posit that the switch to the ECL model in the bank financial reporting system improves borrowers' investment efficiency.

Empirically, the shift from the ICL to the ECL model provides an opportunity to use a difference-in-differences research design to better identify the causal effects of changes in bank

[4] The European Systematic Risk Board (2017) notes that banks' credit risk monitoring systems will improve in the post-ECL model mainly because the ECL model positively affects banks' credit management and governance systems.

monitoring of borrowers due to changes in bank financial reporting practices. We use a group of treatment firms from IFRS 9-adopting countries and control firms from non-adopting countries. To reduce the concern that our results could be due to time-invariant firm-level characteristics and time trends, we include firm and year fixed effects in our regression specification. Using data from 56 countries over a 4-year window (2016–2019), which includes a pre- (2016–2017) and a post-IFRS 9 adoption (2018–2019) period, we document that the treatment firms' investment efficiency, as proxied by investment-*q* sensitivity, increases in the post-IFRS 9 period. This finding is consistent with our hypothesis that the ECL model encourages banks to monitor borrowers' investments more closely, which in turn enhances the borrowers' investment efficiency. To further ensure that the ECL model drives this increased sensitivity, we conduct the standard parallel trends test for a difference-in-differences research design and observe a difference in investment-*q* sensitivity between the treatment and control firms only during the post-IFRS 9 period. Moreover, our result is robust to alternative samples and alternative model specifications. We also use the Oster (2019) test to evaluate the omitted variable concern, and the results suggest that our finding is unlikely to be affected by omitted variables.

To further analyze the mechanisms through which the switch to the ECL model affects borrowers' investment efficiency, we conduct three tests. The first test aims to provide evidence supporting our main argument that banks monitor borrowers more closely under the ECL regime. We conduct this test at both the bank and loan level. Using bank-level data from BankFocus, we document that the banks have fewer nonperforming loans in their portfolios after switching to the ECL model. Using loan contracts from the DealScan database, we examine how the ECL model affects loan contracting terms, and we find an increased use of monitoring mechanisms in loan contracts. Specifically, we document an increased use of performance pricing provisions. These results suggest that banks monitor borrowers more closely under the ECL regime, supporting our main argument. Second, to validate whether the ECL model indeed encourages banks to monitor borrowers' investments and thereby increases borrowers' investment efficiency, we examine whether the regime change has a stronger effect on borrowers that are more dependent on bank debt. We expect banks to have more incentive and even more leverage to monitor firms with more bank debt. Indeed, we document a stronger effect of IFRS 9 adoption on investment-*q* sensitivity for firms that depend heavily on bank debt. Finally, we test the moderating effect of bank regulation. Intuitively, the banks affected by the regime change should monitor borrowers even more closely when facing tighter monitoring by regulators. In line with our expectation, we find a greater increase in investment-*q* sensitivity after IFRS 9 adoption in the countries where banks are strictly monitored. This finding is consistent with that of López-Espinosa et al. (2021), who document that IFRS 9 has a more pronounced effect on loan loss provision informativeness in countries with stringent bank supervision.

Finally, we conduct one supplementary test—an out-of-sample test to explore whether more timely loan loss recognition under the ICL regime is associated with higher investment-*q* sensitivity. Earlier studies on the consequences of loan loss recognition rely on cross-sectional variation in loan loss recognition timeliness (LLRT) under the ICL model (e.g., Beatty and Liao 2011; Bushman and Williams 2012; Akins, Dou, and Ng 2017). Following this literature, we construct several country-level measures to capture the LLRT of each country's banking system. We find a positive association between LLRT in the banking systems and the borrowers' investment-*q* sensitivity, which is consistent with our findings on the switch from the ICL to the ECL model.

We contribute to the literature in two important ways. First, our results extend the research on the consequences of financial reporting in banks' role as delegated monitors of borrowers. LLRT receives significant attention from academics, regulators, and practitioners

(Beatty and Liao 2014). The academic literature focuses on its disciplinary effects on lending due to the strict regulatory and stakeholder monitoring of banks' loan losses (Beatty and Liao 2011; Bushman and Williams 2012; Akins et al. 2017). Our paper complements and contrasts with this literature by highlighting how timely loan loss recognition in principle requires banks to monitor borrowers more closely and thus has disciplinary effects on borrowers' investments, whose returns are an important source of money for interest payments and loan repayments. In doing so, we offer evidence relevant to the theoretical role of banks as the delegated monitors of borrowers (Diamond 1984; Fama 1985). Despite the voluminous empirical literature on topics related to this role (e.g., Hoshi, Kashyap, and Scharfstein 1990a, 1990b; Wang and Xia 2014; Vashishtha 2014), there is limited evidence on how banks' reporting systems help to fulfill it (Beatty, Liao, and Weber 2012; Carrizosa and Ryan 2017).[5] We contribute to this body of literature by providing evidence of a specific and important mechanism, namely banks switching to the ECL model to account for expected loan losses. We also show how the regulation of delegated monitors can moderate the impact of the mechanism.

Our second contribution relates to using the switch to the ECL model to examine how banks' LLRT affects borrowers. Regulators, practitioners, and academics have an ongoing interest in understanding the costs and benefits of the ECL model. The new model is more forward-looking and helps mitigate concerns about "too little, too late" provisioning, procyclicality, and financial instability. However, it is criticized for imposing high compliance costs on banks and granting them too much discretion over estimating credit losses. We further explore the ECL model and show evidence of its consequences beyond the banking system per se. Specifically, in contrast to other research focusing on banks (e.g., Kim et al. 2021b; López-

[5] Vashishtha (2014) uses covenant violations to provide evidence on how firms make disclosure decisions in the presence of enhanced bank monitoring. He finds that firms reduce disclosure following covenant violations and attributes this finding to a delegation of monitoring to banks by shareholders who consequently demand less disclosure. In a similar spirit, our paper uses the switch to the ECL model to examine how enhanced bank monitoring has real effects on borrowers in terms of their investment efficiency.

Espinosa et al. 2021; Wheeler 2021), we extend the nascent literature on how the switch to the ECL model affects borrowers (Giner and Mora 2019; Kim et al. 2021a; Li et al. 2022). For example, Kim et al. (2021a) find that loan contracting terms becomes more stringent after IFRS 9 adoption, consistent with borrowers being monitored more stringently after a shift in financial reporting that requires banks to monitor borrowers more intensely. Li et al. (2022) find that IFRS 9 adoption reduces borrowers' reliance on bank debt relative to public debt, consistent with some firms shifting their credit financing from bank financing to public debt financing to avoid costly accounting-driven bank monitoring. Our paper complements the literature by showing the positive effect of IFRS 9 on borrowers' corporate investment activities, as opposed to borrowers' financing choices between bank and public debt. In doing so, we add to a growing body of literature on the role of accounting in corporate investments (see, e.g., the survey by Roychowdhury et al. 2019). In particular, we provide the novel insight that the reporting system of a firm's contracting party (i.e., the lender) can affect the firm's investment efficiency.

2. Institutional Background and Hypothesis Development

2.1. The Switch from the ICL to the ECL Model

In the aftermath of the recent financial crisis, the delayed recognition of credit losses sparked heated debate (Beatty and Liao 2014; Wheeler 2021). Critics argued that the ICL model in IAS 39 substantially contributed to delays in the recognition of loan losses (Bischof Laux, and Leuz 2021; López-Espinosa et al. 2021). The International Accounting Standards Board responded by proposing the more forward-looking ECL model in newly issued IFRS 9 (López-Espinosa et al. 2021). IFRS 9 became effective for periods beginning on or after January 1, 2018 and most IFRS-adopting countries adopted this standard when it became effective.[6] The ECL regime has led to a shift in banks' loan loss accounting. Whereas the ICL

[6] A similar standard in the US Generally Accepted Accounting Principles called the current expected credit loss model was introduced by the Financial Accounting Standards Board and became effective in 2020.

model records loan losses based on objective evidence of impairment, the ECL model requires that "banks … provision for expected credit losses from the time a loan is originated, rather than awaiting 'trigger events' signaling imminent losses" (Cohen and Edwards 2017, p. 39). Building loan loss provisions before risks become actual impairments makes banks more resilient to economic recessions and crises (European Central Bank 2019).

The ECL model has many implications, partly because loan loss provisioning is the largest accrual in banks' financial statements (Beatty and Liao 2014). A rule change thus could significantly affect banks and the overall economy. Perhaps unsurprisingly, given the nature and importance of the switch to the ECL model, the related literature focuses on bank outcomes. Lu and Nikolaev (2019) develop models for estimating future losses, and a related theory paper shows that under ECL, loan loss provisions increase suddenly when the economy shifts from expansion to recession (Abad and Suarez 2018). Buesa, Población, and Tarancón (2019) show that the ECL model is less procyclical than is the ICL model. Kim et al. (2021b) find that the ECL model leads to increased loan loss recognition timeliness. López-Espinosa et al. (2021) find that relative to the ICL model, the ECL model is more predictive of expected bank risk. In contrast to the extant literature, our paper studies the spillover effects of the ECL model on an important borrower outcome, investment efficiency.

2.2. Hypothesis Development

We posit that to the extent that banks' accounting practices affect their monitoring of borrowers, these practices also might affect borrowers' corporate decisions (e.g., investment). In this study, we examine whether the new accounting rule for banks' loan loss provisioning affects client firms' (i.e., borrowers') investment efficiency. To the extent that expected loan losses are based on borrowers' anticipated conditions, the transition from the ICL to the ECL model should affect borrowers' actions. Specifically, if the ECL model requires banks to record loan losses in a timely manner, which in turn requires close monitoring of borrower firms, then this practice should impact firms' investment efficiency.[7] Figure 1 illustrates how we expect the switch to the ECL model to affect investment efficiency.

A large body of literature emphasizes banks' monitoring role (e.g., Diamond 1984; Hoshi et al. 1991; Besanko and Kanatas 1993). Prior research, both theoretical (e.g., Diamond 1984) and empirical (e.g., Freixas and Rochet 2008), shows that banks serve as delegated monitors to discipline inefficient borrowers or those that fail to pursue profit goals (Stiglitz and Weiss 1981). Rajan (1992) posits that banks can use their knowledge of borrowers' investments to discourage negative net present value projects, for example, by demanding immediate loan repayment. In the same vein, earlier literature (e.g., Diamond 1984; Fama 1985; Boyd and Prescott 1986) argues that by collecting and evaluating information about borrowers, banks provide valuable monitoring and discipline via contractual remedies, such as rationing capital, refusing further credit, accelerating outstanding loans, and foreclosing collateral. In this way, banks can influence firms' investment behavior directly by amending contracts and indirectly by exerting informal influence on corporate governance (Nini, Smith, and Sufi 2012).

We hypothesize that the ECL model increases banks' monitoring of borrowers because the banks must make loan loss provisions at earlier stages of the loan (i.e., Stages 1 and 2), rather than waiting until Stage 3 when the loan becomes non-performing (PWC 2014, 2015, 2017; Deloitte 2019).[8] For example, PWC (2017) highlights the following:

> A critical and highly judgemental area in the calculation of the ECL is the assessment of whether there has been a "significant increase in credit risk" since initial recognition. If such an increase has occurred, an entity is required to recognise lifetime expected credit losses rather than just 12-month expected credit losses. (PWC, 2017, p. 2)

[7] Similarly, anecdotal evidence indicates that under the ECL model, banks consistently monitor borrowers' loan repayment behavior (Ezio et al. 2021) and regularly match the macroeconomic situations and borrower attributes to better ascertain the level of credit risk (Bank for International Settlements 2015).

[8] Stage 1 financial instruments are those for which credit risk does not significantly increase after initial recognition or those with low credit risk on the reporting date; for these assets, 12-month ECL is recognized. Stage 2 financial instruments have had a significant increase in credit risk since initial recognition but no objective evidence of impairment; for these assets, lifetime ECL is recognized. Stage 3 financial instruments have objective evidence of impairment at the reporting date; for these assets, lifetime ECL is recognized.

Anecdotal evidence from banks' public disclosure suggests that under IFRS 9, they must stay vigilant in monitoring borrowers' condition. In its report on the transition to IFRS 9 Financial Instruments dated January 1, 2018, HSBC Holdings plc (2018) explains loan loss reserves under the ICL and ECL regimes and breaks down the reserves for loans in Stage 1, 2, or 3, including the effect of IFRS 9 on its business model:

> Exposures in certain industry sectors, in particular those most sensitive to changes in economic conditions, will be affected to a greater degree under IFRS 9. However, we have established credit risk management processes in place and we actively assess the impact of economic developments in key markets on specific customers, customer segments or portfolios. If we foresee changes in credit conditions, we will take mitigating action, including the revision of risk appetites or limits and tenors, as appropriate. In addition, we will continue to evaluate the terms under which we provide credit facilities within the context of individual customer requirements, the quality of the relationship, local regulatory requirements, market practices and our local market position. (p. 2)

To the extent that the ECL model increases banks' monitoring of borrowers, we expect borrowers' investments to be more responsive to opportunities that increase the firm's net present value. To increase responsiveness, borrowers must invest more (less) in good (bad) investments.[9] We posit that enhanced bank monitoring can increase investment responsiveness in two ways: by reducing moral hazard problems that hinder financing of investment opportunities, and by enhancing relationship banking that facilitates the conversion of investment opportunities into investments.

First, we discuss how enhanced bank monitoring can mitigate moral hazards in lending, which ex-ante can make banks unwilling to finance borrowers' investments. Diamond's (1984) delegated monitoring framework provides an intuitive explanation for the existence of financial intermediaries based on potential moral hazard problems. In practice, moral hazards in lending can occur in a variety of ways. A borrower might engage in empire building by investing borrowed funds in projects with no or even negative returns, which in turn increases the

[9] Investing in bad investments can reduce the financial resources available to invest in good investments, thus hindering responsiveness to investment opportunities that could increase the firm's net present value.

probability of borrower default and the bank's subsequent loss (Jensen 1986). A borrower also might invest in riskier projects than what the loan contract specifies (Eisdorfer 2008).[10] Finally, prior studies suggest that effective bank monitoring can restrict executive perquisites and promote value-creating investment (Lin, Zhang, and Zhu 2009; Luo, Zhang, and Zhu 2011). As a form of corporate governance, bank monitoring also can discipline borrowers so that they invest more when good investment opportunities arrive, as investment returns contribute towards the loan repayment and thus, reduce loan default likelihood.

Second, banks' increased monitoring can enhance relationship lending, which in turn, can help borrowers to identify and convert investment opportunities. Relationship lending, which involves banks generating additional value by engaging with, learning about, and providing business advice to borrower, is important in many parts of the world (Boot 2000; Greenbaum, Thakor, and Boot 2020). As the classical and seminal book by Schumpeter (1939, p. 116) describes, "…the banker must not only know what the transaction is which he is asked to finance and how it is likely to turn out but he must also know the customer, his business and even his private habits, and get, by frequently 'talking things over with him,' a clear picture of the situation."

When banks closely monitor borrowers, including their macroeconomic environments, they can help borrowers uncover and respond to good investment opportunities (Beck et al. 2018; Banerjee, Gambacorta, and Sette 2021). Banks can then use their informational and financial resources to help borrowers finance those investments (Hoshi et al. 1990a, 1991; Schenone 2010; Frattaroli and Herpfer 2021), such as through syndicated loans (Güner, Malmendier, and Tate 2008; Houston, Lee, and Suntheim 2018; Gustafson, Ivanov, and Meisenzahl 2021). Khan et al. (2021) further find that firms entering a strategic partnership

[10] Donovan and Martin (2019) find that reduced bank monitoring leads to borrowers making risky investments and engaging in other actions that negatively affect lenders.

receive lower interest rates from banks that have previously lent to the strategic partners, compared to loan offers from other banks, indicating that strategic alliances are another channel through which lending relationships that facilitate investments form.

In sum, based on the view that the ECL model enhances bank monitoring, which in turn reduces moral hazard problems and enhances relationship banking, we predict that borrowers' investment activities will be more responsive to investment opportunities with the switch to the ECL model for bank financial reporting. We state our central hypothesis as follows:

Hypothesis: The switch to the ECL model under IFRS 9 increases borrowers' investment efficiency.

We emphasize that this hypothesis is not without some tension. For example, intense monitoring of banks can lead to hold-up problems for borrowers, which might in turn adversely affect their investment efficiency (Rajan 1992; Mahrt-Smith 2006; Roberts and Sufi 2009). In another example, some borrowers might avoid costly bank monitoring by switching to other forms of debt financing, such as bond issuance (Lin et al. 2013; Li et al. 2022). In this case, the switch to the ECL model might not affect investment efficiency, at least for borrowers who can obtain alternative financing.

3. Research Design

3.1. Sample

We obtain our international data from Compustat, including the North American and Global datasets. We exclude financial industry firms (SIC codes 6000–6999), regulated utilities (4900–4999), and government entities (9000–9999). Following standard practice in the corporate investment literature (e.g., Peters and Taylor 2017), we also exclude firms with less than \$5 million in physical capital.[11] To mitigate the borrower's and bank's selection issue

[11] Specifically, we require our sample firms to have no less than \$5 million in net property, plant, and equipment assets at the end of fiscal year 2017 (i.e., the year prior to IFRS 9 adoption). We show in column (3) of Table 4, Panel A that our results are robust if we include firms with physical assets of less than \$5 million.

about whether to engage in bank debt contracting, we rely on the Capital IQ database to identify firms' debt structures, and we restrict our sample to firms with outstanding bank debt just prior to IFRS 9 adoption. In other words, the firms in our sample must have positive bank debt at the end of 2017. Our sample period covers a four-year window (2016–2019), including a pre- (2016–2017) and post-adoption (2018–2019) period. After dropping observations with missing values, our final sample comprises 59,079 firm-year observations with 15,373 unique firms from 56 countries.[12]

We present the sample composition by country in Table 1, Panel A. After searching for information on the Internet, particularly on the International Accounting Standards Board website, we identify that in 39 of 56 countries/regions, the banking industry switched from the ICL to the ECL model by adopting IFRS 9 on January 1, 2018. These 39 countries/regions serve as our treatment group, and the remaining 17 serve as our control group. As shown in Panel B, each year in our sample period 2016–2019 contributes around 25 percent of the observations in our final sample and in each year, the treatment sample size (*IFRS9* = 1) is slightly larger than the control sample size (*IFRS9* = 0).

3.2. Investment and the Tobin's q Measure

To study the impact of a lender's reporting system on its borrowers' investment efficiency, we focus on the effect of IFRS 9 adoption on firms' investment-q sensitivity. Because intangible capital has grown in importance for modern firms and our study is based on a recent sample period, we use Peters and Taylor's (2017) measures of total investment and total q to capture investment-q sensitivity, which account for both physical and intangible capital.[13]

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[12] We rely on Compustat item *loc* (Current ISO Country Code-Headquarters) to identify firms' headquarters location.

[13] Peters and Taylor (2017) provide a detailed description in their paper and its Appendix B on how to construct the total investment and total Tobin's q measures. They also kindly share these measures for US firms through Wharton Research Data Services. Given that their shared measures are available only for US firms and are updated only to 2017, for the sake of consistency, we construct our own measures for our entire international sample. Our

First, we need the replacement cost of total capital, which consists of physical and intangible capital. We measure the physical capital replacement cost as the gross value of property, plant, and equipment (Compustat item *ppegt*). Estimating intangible capital's replacement cost is more complex. We measure the replacement cost of a firm's intangible capital as the sum of the end-of-period stock of externally purchased and internally created intangible capital. The amount of externally purchased intangible assets is recorded in a firm's balance sheet as "Intangible Assets" (Compustat item *intan*). In contrast, no balance sheet item captures internally created intangible capital, specifically knowledge and organization capital. Hence, we use the perpetual inventory method to estimate it based on firms' research and development (R&D) expenditure and their selling, general, and administration (SG&A) expenses, which respectively reflect firms' knowledge and organization capital.

Specifically, we use the following formula to derive a firm's knowledge capital:

$$G_{i,t} = (1 - \delta) \times G_{i,t-1} + R\&D_{i,t}, \tag{1}$$

where $G_{i,t}$ represents firm i's accumulated knowledge capital up to year t. As for the depreciation rate (δ) of knowledge capital, we use a rate of 15 percent for all our sample firms.[14] We use Compustat item *xrd* to measure a firm's annual R&D spending ($R\&D_{i,t}$); when it is missing, we set $R\&D_{i,t}$ to 0. We iterate Eq. (1) using data going back to 1987, the earliest year available in the Compustat Global database. In the beginning of 1987 or when a firm first appears in the Compustat database, we set $G_{i,0}$ to 0 by assuming zero initial capital stock.[15]

measures for US firms from 1987–2017 are highly comparable to the shared measures (e.g., the correlation coefficient between the two sets of derived intangible capital is as high as 99 percent, and the correlation coefficient between the two sets of total q measures is as high as 95 percent).

[14] Ideally, the depreciation rate should be specific to a given country-industry. However, to the best of our knowledge, no such international data exist. Peters and Taylor (2017) also use a depreciation rate of 15 percent for US industries without an available industry-specific deprecation rate.

[15] Peters and Taylor (2017) estimate G_{i0} by estimating a firm's annual R&D spending from its founding year to its first appearance in Compustat. They also show that the simpler measure, assuming zero initial capital stock, is a reasonable alternative proxy. As they document, the simpler measure produces an even stronger investment-q sensitivity in the US sample from 1975–2011.

We estimate a firm's organization capital accumulated through SG&A spending by using similar iterations in Eq. (1). Prior literature suggests that some proportion of SG&A spending represents a firm's investment in organization capital, and we treat 30 percent of SG&A as an organization's capital investment.[16] As for the depreciation rate of organizational capital, we use a rate of 20 percent. In line with the estimation of knowledge capital, we assume that a firm has zero initial organization capital when it first appears in the Compustat database.

We then compute the replacement cost of total capital by summing physical and intangible capital. With this replacement cost, we are now ready to compute our measures of total investment (I) and total q (Q). We measure a firm's total investment as capital expenditure (*capx*) plus R&D expenditure (*xrd*) plus 30 percent of SG&A expenses (*xsga* minus *xrd*).[17] We then scale this measure by the replacement cost of total capital in the previous year to create I, which we use as the dependent variable in our baseline regression specification (see Eq. (2)). We measure Q as the ratio of the firm's market value to the replacement cost of total capital. We calculate a firm's market value as the market value of its outstanding equity (Compustat items *prcc_f* times *csho* for firms in the Compustat North American database and *prccd* of a firm's primary issue times *cshoi* for firms in the Compustat Global database), plus the book value of its total debt (*dltt* plus *dlc*), and minus its current assets (*act*). The coefficient on Q in our baseline regression specification (see Eq. (2)) captures investment-q sensitivity.

3.3. Model Specification

Our identification strategy exploits IFRS 9 adoption as a shock to banks' financial reporting systems. Although IFRS 9 became effective on January 1, 2018, some countries did not adopt it during our 2016 to 2019 sample period. We follow Jayaraman and Wu (2019) and

[16] The Compustat item for SG&A expenses (*xsga*) includes R&D spending (*xrd*), so we subtract *xrd* from *xsga* and then multiply the result by 30 percent to obtain the annual investment in organization capital.
[17] Note that the Compustat item *xsga* includes *xrd*.

specify the following difference-in-differences model to study the impact of IFRS 9 adoption on borrowers' investment-q sensitivity:

$$I = \beta_0 + \beta_1 Q \times IFRS9 \times POST + \beta_2 Q + \beta_3 IFRS9 \times POST + \beta_4 Q \times IFRS9 + \beta_5 Q \times POST + \beta_6 SIZE + \beta_7 TANGI + \beta_8 SLACK + \beta_9 LOSS + \beta_{10} ZSCORE + \beta_{11} KSTR + \beta_{12} INDKSTR + \beta_{13} GDPPC + \beta_{14} INFLATION + \beta_{15} UNEMPR + \beta_{16} CBKCREDIT + \beta_{17} CBKCAPR + \beta_{18} CBKNIM + Firm\ F.E. + Year\ F.E. + \varepsilon. \quad (2)$$

In Eq. (2), the dependent variable (*I*) is a firm's total investment in year *t* scaled by the lagged replacement cost of total capital, as previously defined. To test our central hypothesis, we focus on the three-way interaction term *Q* × *IFRS9* × *POST*.[18] *Q* is the firm's total *q* at the end of year *t*−1, as previously defined. *IFRS9* is an indicator variable that equals 1 if the firm is headquartered in a treatment country that adopted IFRS 9 in January 2018 and 0 otherwise. *POST* is an indicator variable that equals 1 for the 2018–2019 post-adoption period and 0 for the 2016–2017 pre-adoption period. All control variables in Eq. (2) are lagged by one year, which is consistent with prior literature on investment-*q* sensitivities (e.g., McLean et al. 2012; Jayaraman and Wu 2019). The neoclassical theory of investment predicts that corporate investment will be sensitive to investment opportunities, as captured by Tobin's *q*. We therefore expect the coefficient on *Q* (β_2) to be significantly positive. A significantly positive coefficient on the three-way interaction term (β_1) would support our hypothesis that the switch to the ECL model under IFRS 9 enhances firms' investment-*q* sensitivity.

Following the literature (e.g., Biddle, Hilary, and Verdi 2009; Chen et al. 2011; Cheng, Dhaliwal, and Zhang 2013; García Lara, García Osma, and Penalva 2016; Jayaraman and Wu 2019), we control for a series of firm-level characteristics in this regression model. First, we control for firm size (*SIZE*), defined as the natural logarithm of total assets, and asset tangibility

[18] The three-way interaction term in our main specification captures the average effect of the switch to the ECL model on borrowers' investment-*q* sensitivity. This type of research design essentially assumes that borrowers within a country are subject to the same effects. However, this assumption is unlikely to be true. Therefore, we later conduct several analyses to investigate the conditions under which the effect of the switch will be stronger.

(*TANGI*), calculated as the net value of property, plant, and equipment divided by total assets. We also control for firm financial conditions, including financial slack (*SLACK*), an operating loss dummy (*LOSS*), and Altman's (1968) Z-score (*ZSCORE*). Based on Biddle et al. (2009), financial slack is defined as the ratio of cash and short-term investment to the net value of property, plant, and equipment. Following Biddle et al. (2009), Cheng et al. (2013), and García Lara et al. (2016), we also control for capital structure at the firm and industry levels. We define firm-level capital structure (*KSTR*) as long-term debt divided by the sum of long-term debt and the market value of equity. The industry-level capital structure (*INDKSTR*) takes the mean of *KSTR* for firms in the same SIC 3-digit industry, country, and year.

To account for variations in economic conditions across countries, we control for the natural logarithm of GDP per capita (*GDPPC*), annual inflation rate (*INFLATION*), and unemployment rate (*UNEMPR*). We also include several important characteristics of banking systems to control for the potential effect of debt supply on corporate investment. Specifically, we control for the country-level aggregated bank credit to private sectors (*CBKCREDIT*), the aggregated bank capital ratio (*CBKCAPR*), and bank net interest margin (*CBKNIM*).[19] Finally, we include firm and year fixed effects to mitigate the omitted variable problem.[20] In the regression analysis, we adjust standard errors for country-level clustering because the shock in our setting (i.e., IFRS 9 adoption) is at the country level. We winsorize all continuous variables at the 1st and 99th percentiles. Appendix A summarizes the variable definitions.

3.4. Descriptive Statistics

Table 2 presents the descriptive statistics for our main regression variables. In our sample, the mean (median) annual total investment (*I*) is 12.6 percent (10.3 percent) of total capital stock. The distribution of total *q* (*Q*) is comparable to that reported in Peters and Taylor

[19] In a robustness check, we show that our inference remains unchanged when we include country × year fixed effects to absorb all time-variant country-level factors. See column (1) of Table 4 Panel B.

[20] Because the main effects of *IFRS9* and *POST* are respectively absorbed by firm and year fixed effects, we omit these two variables from Eq. (2).

(2017), with a mean (median) value of 1.145 (0.549). As shown, 58.9 percent of firm-year observations are from treatment countries (*IFRS9* = 1), and nearly 50 percent of our sample is in the post-adoption period (*POST* = 1). The statistics for some of our control variables are comparable to those in prior literature (e.g., Biddle et al. 2009; Chen et al. 2011; García Lara et al. 2016). For example, tangible assets make up 32.9 percent of total assets (*TANGI*) on average, and 21.2 percent of firm-year observations show an operating loss (*LOSS* = 1).

4. Empirical Results

4.1. Main Results and Parallel Trend

Table 3 presents the results of testing our central hypothesis by running the regression specified in Eq. (2). The dependent variable is firms' annual investment, and the independent variables include the lagged total q (Q), the lagged control variables, and interaction terms for Q, *IFRS9*, and *POST*. The coefficient on Q captures the classical investment-q sensitivity, which prior theory and empirical studies indicate should be significantly positive (e.g., Tobin 1969; Hayashi 1982; McLean et al. 2012; Shroff 2017). We focus on the three-way interaction term Q × *IFRS9* × *POST*, for which a significantly positive coefficient would suggest that the switch to the ECL model under IFRS 9 enhances firms' investment-q sensitivity.

In column (1), the coefficient on Q is significantly positive, which is consistent with the classical investment-q literature and suggests that corporate investment for the firms in our international sample is sensitive to investment opportunities captured by Tobin's q. More importantly, we find a significantly positive coefficient on Q × *IFRS9* × *POST* (0.0030) after controlling for a series of firm- and country-level characteristics, and this coefficient is significantly different from 0 at the 1 percent level (t-value = 3.09).[21] This result supports our

[21] Our results are not driven by the inclusion of control variables or fixed effects. In an untabulated test, we get qualitatively similar results when we exclude all control variables and fixed effects.

central hypothesis that the switch to the ECL model leads to more intense monitoring of borrowers, which in turn enhances their investment-q sensitivity.

In column (2), we test the parallel assumption of our difference-in-differences design and investigate the dynamic effects of IFRS 9 adoption on investment-q sensitivity. Our four-year sample period covers 2016 to 2019. We use 2016 as the benchmark year and create three indicator variables for 2017, 2018, and 2019 (*T2017*, *T2018*, and *T2019*), respectively. We replace all *POST* variables in Eq. (2) with these three indicators for year and rerun the regression. The coefficient on *Q* × *IFRS9* × *T2017* is statistically insignificant, which supports the parallel trend assumption by suggesting that the difference in investment-q sensitivity between the treatment and control groups in the pre-adoption year of 2017 is not statistically different from the difference in the benchmark year of 2016. In contrast, we find significantly positive coefficients on *Q* × *IFRS9* × *T2018* and *Q* × *IFRS9* × *T2019*, suggesting that treatment firms' investment decisions become more sensitive to investment opportunities immediately after IFRS 9 adoption.

4.2. Robustness Checks

4.2.1. Alternative Samples

First, we check whether our results are robust to alternative samples. IFRS 9 became effective on January 1, 2018, but firms may need time to adjust their investment decisions. In column (1) of Table 4, Panel A, we exclude fiscal year 2018 and continue to find significantly positive results. The exclusion of 2018 makes our sample unbalanced between the pre- and post-adoption periods, so we further exclude fiscal year 2016 in column (2). In this way, we essentially conduct a difference-in-differences analysis based on one-year observations in both the pre- and post-adoption periods. Our main results hold, even though the sample size decreases by half in column (2). In our main analysis, we follow Peters and Taylor (2017) and restrict our sample to firms with no less than $5 million in physical capital. As shown in column

(3), our results are robust to a larger sample that includes firms with less than \$5 million in physical assets. Taken together, our main findings are robust to several alternative samples. In column (4), we conduct a falsification test by counterfactually assuming that IFRS 9 adoption occurred in 2016 for the treatment countries; then, we repeat our difference-in-differences analysis based on a four-year sample period 2014–2017. In column (5), we counterfactually assume 2014 as the adoption year and repeat our analysis on the sample period from 2012–2015. Both falsification tests yield insignificant coefficients on the three-way interaction term, suggesting that our main findings are driven by the actual adoption of IFRS 9.

4.2.2. Alternative Model Specifications

We also check whether our results are sensitive to model specification. In our main specification, we include firm and year fixed effects. In column (1) of Table 4, Panel B, we show that our results hold if we replace the year fixed effects with country × year fixed effects. Country × year fixed effects can absorb all time-variant country-level factors, including economic condition and characteristics of banking system in each country.[22] Therefore, our results are unlikely to be affected by country-level debt supply shocks. Our sample is unevenly distributed across countries (see Table 1, Panel A), which could bias our findings towards larger countries. To address this concern, we use a weighted least square regression in column (2), where the weight for each country equals 1 divided by the number of observations in the country. In this way, each country contributes equally to the average effects captured by the regression coefficients. The findings remain unchanged, suggesting that our main results are not driven solely by countries with a high number of observations.

To address the concern of imbalanced sample size between treatment and control groups, we use propensity score matching to construct a matched sample. Specifically, we

[22] In column (1) of Table 4, Panel B, *IFRS9* × *POST* and all country-level control variables are absorbed by country × year fixed effects.

estimate propensity scores based on firm- and country-level characteristics in 2017 and then do a one-to-one match, without replacement, between treatment and control firms. Using this matched sample, we find qualitatively the same results in column (3). In column (4), we also check whether our results are robust after controlling for borrowers' debt structure (*DEBTSTR*), which might be affected by the switch from the ICL to the ECL model (Li et al. 2022). *DEBTSTR* is defined as the ratio of bank debt to the balance of total debt. We control for *DEBTSTR* and its interaction term with *Q* and do not find significant coefficients on either, but we continue to find a significantly positive coefficient on $Q \times IFRS9 \times POST$. Taken together, our results in Table 4, Panel B show that our main findings are robust to various alternative model specifications.

4.2.3. Omitted Variable Concern

We acknowledge that omitted variables could bias our results. To mitigate this issue, we include in our baseline model a series of firm- and country-level control variables and firm fixed effects. Nevertheless, our results still could reflect effects from unobserved firm and country attributes. In this subsection, we conduct a recently developed technique to assess the extent of bias from correlated omitted variables. Specifically, we use the Oster (2019) test to evaluate the sensitivity of our main results to unobservable selection and coefficient stability. This test has been used in many recent papers (e.g., Call et al. 2018; Heimer, Myrseth, and Schoenle 2019; Argyle et al. 2021; Bernard, Kaya, and Wertz 2021). Building on Altonji, Elder, and Taber's (2005) proportional selection relationship, Oster (2019) proposes a test to evaluate omitted variable bias by incorporating the coefficient and R-square movement between uncontrolled and controlled regression models. The Oster (2019) test generates the coefficient of proportionality, δ, based on both coefficient and R-square movements.[23] A higher value of δ indicates a smaller likelihood of omitted variables having significant effect. For

[23] Oster (2019) provides the Stata command "psacalc" to perform the test.

example, a δ of 1.00 indicates that omitted variables need to be as important as observables to overturn the results. Therefore, values of δ greater than 1.00 suggest a robust result.

The Oster (2019) test relies on the maximum R-square, obtained from a hypothetical regression model that includes all observable and unobservable controls. Based on her research, Oster (2019) recommends that researchers estimate the maximum R-square as 1.3 × the R-square from the regression model with a full set of observable controls. We follow this recommendation and present the results in Table 4, Panel C. We first present the coefficient and R-square movements. We start by estimating the model without controls and fixed effects. We get a coefficient of 0.0043 on *Q* × *IFRS9* × *POST* and an R-square of 0.123.[24] We then add controls and fixed effects into the regression model and get our baseline results: the coefficient decreases to 0.0030, and R-square increases to 0.755.[25] Assuming that the maximum R-square we can obtain is 0.981 (= 1.3 × 0.755), we get a δ of 2.781, which is much larger than 1.00, suggesting that our results are unlikely to be driven by omitted variable bias. In addition, we follow Argyle et al. (2021) and use the Oster (2019) technique to estimate the bias-adjusted coefficient on *Q* × *IFRS9* × *POST*. We find that the bias-adjusted coefficient is 0.0023, which is within the confidence interval of our baseline results.[26] Overall, the results increase confidence in the robustness of our findings.

5. Mechanisms

5.1. Test of Monitoring Channel

Our main results suggest that bank monitoring is an important channel through which the shift to the ECL model can affect borrowers' investment-*q* sensitivity. However, it is difficult for a researcher to directly measure bank monitoring because bank monitoring takes

[24] Specifically, we start with a model that controls only for *Q*, *IFRS9* × *POST*, *Q* × *IFRS9*, and *Q* × *POST* because our variable of interest is the three-way interaction term *Q* × *IFRS9* × *POST*.
[25] Note that in Table 3 column (1), where we present our baseline results, we report the adjusted R-square, which is slightly smaller than the raw R-square reported here.
[26] In our baseline results, the 95 percent confidence interval of the three-way interaction term *Q* × *IFRS9* × *POST* is [0.0011, 0.0050].

many forms that are not observable and/or measurable by the researcher, e.g., private communication between the bank and its borrowers, greater bank attention on the economic conditions surrounding the borrowers, and corporate site visits (e.g., Carrizosa and Ryan 2017; Gustafson et al. 2021). Hence, it is difficult to empirically validate whether the shift to the ECL model indeed increases bank monitoring, although the nature of the ECL model and anecdotes, as discussed earlier, does provide support for the link between the shift to the ECL model and bank monitoring. Supporting the monitoring channel is a recent paper by Li et al. (2022), which find that the shift to the ECL regime leads to a shift in borrowers away from bank debt towards public bonds, especially for borrowers with greater access to bond markets. This finding is consistent with at least some borrowers engaging in avoidance of costly bank monitoring after the shift to the ECL model.

In this subsection, we conduct two analyses to indirectly test the effect of IFRS 9 adoption on bank monitoring. The first one is a bank-level analysis, in which we test the monitoring channel by focusing on bank's nonperforming loans. We argue that the ECL model incentivizes banks to closely monitor borrowers. Hence, we expect fewer nonperforming loans after IFRS 9 adoption. To test the effect of IFRS 9 adoption on bank's nonperforming loans, we obtain international data from BankFocus and conduct a bank-level difference-in-differences analysis from 2016–2019. Our treatment sample consists of banks headquartered in countries/regions that adopt IFRS 9 on January 1, 2018. Banks headquartered in a non-IFRS 9-adopting country are considered the control sample. After dropping observations with missing values for the regression variables, our final sample has 49,402 bank-year observations. We use the following OLS model to test the effect of IFRS 9 adoption on nonperforming loans:

$$\begin{aligned} NPL1 = {} & \beta_0 + \beta_1 IFRS9 \times POST + \beta_2 BKSIZE + \beta_3 BKCAPR + \beta_4 BKROE + \beta_5 BKNIM + \\ & \beta_6 GDPPC + \beta_7 INFLATION + \beta_8 UNEMPR + \beta_9 CBKCREDIT + \beta_{10} CBKCAPR + \\ & \beta_{11} CBKNIM + \text{Bank F.E.} + \text{Year F.E.} + \varepsilon. \end{aligned} \tag{3}$$

In Eq. (3), the dependent variable, *NPL1*, is defined as banks' nonperforming loans in year *t* scaled by total outstanding loans. To ensure that our results are not driven by a scaling effect, we also use banks' total assets to scale nonperforming loans (*NPL2*). A significantly negative coefficient on *IFRS9* × *POST* would be consistent with the view that banks increase monitoring after IFRS 9 adoption. We control for several borrower-level characteristics, including bank size (*BKSIZE*), capital ratio (*BKCAPR*), return on equity (*BKROE*), and net interest margin (*BKNIM*). We also include a series of country-level variables to control for cross-country variations in economic conditions and banking systems. All control variables are lagged by one year. Finally, we include bank and year fixed effects and cluster standard errors at the country level.[27]

Table 5 presents the results. In columns (1) and (2), we respectively use *NPL1* and *NPL2* as dependent variables. In both columns, we find significantly negative coefficients on the interaction term *IFRS9* × *POST*, suggesting that banks in IFRS 9–adopting countries experience fewer nonperforming loans in the post-adoption period. We interpret the decrease in banks' nonperforming loans as the result of closer monitoring of borrowers when banks switch to the ECL model.

The second analysis focuses on a monitoring mechanism as indicated by loan contracting terms. We argue that the ECL model incentivizes banks to monitor borrowers to achieve timelier loan loss recognition. In addition to post-loan origination monitoring, banks can take preemptive actions, for example, by adding performance pricing provisions to loan contracts.[28] Performance pricing provisions allow banks to charge higher interest rate when borrowers' condition deteriorates, and thus increases a lender's incentives to monitor.

[27] Because the main effects of *IFRS9* and *POST* are respectively absorbed by bank and year fixed effects, they are omitted from Eq. (3).
[28] Performance pricing provisions link the loan interest rate to the borrower's credit rating and financial ratios throughout the course of loan maturity. When the borrower's creditworthiness declines, performance pricing provisions allow banks to charge higher interest rates on the existing loans (Asquith et al. 2005).

Therefore, inclusion of pricing provisions in loan contracts signals a high level of post-loan origination monitoring of borrowers' conditions and financial policies (Asquith, Beatty, and Weber 2005; Cohen et al. 2022).

To test whether IFRS 9 adoption affects loan contract terms, we obtain international loan contract data from DealScan and conduct a loan-level difference-in-differences analysis from 2016–2019. Using Schwert's (2018) link table, we identify a list of public banks and merge them with Compustat to get their headquarters locations. Our treatment sample consists of loans issued by public banks headquartered in countries/regions that adopt IFRS 9 on January 1, 2018. A syndicated loan issued by a group of banks is assigned to the treatment group if we can identify at least one lead bank headquartered in an IFRS 9-adopting country. We assign a loan to the control group only if all of the loan's lead banks are public banks (so that we can identify locations) and are headquartered in a non-IFRS 9-adopting country. After dropping observations with missing values for the regression variables, our final sample has 9,932 loans. We use the following OLS model to test the effect of IFRS 9 adoption on loan contract terms:[29]

$$\begin{aligned} PERFPRICE = {} & \beta_0 + \beta_1 IFRS9 \times POST + \beta_2 IFRS9 + \beta_3 LOANSIZE + \beta_4 LOANMAT + \beta_5 SIZE + \\ & \beta_6 TANGI + \beta_7 LEV + \beta_8 ZSCORE + \beta_9\, EBITDA + \beta_{10}\, CFOVOL + \beta_{11}\, GDPPC + \\ & \beta_{12} INFLATION + \beta_{13} UNEMPR + \beta_{14} CBKCREDIT + \beta_{15} CBKCAPR + \beta_{16} CBKNIM + \\ & \text{Loan type F.E.} + \text{Loan purpose F.E.} + \text{Industry F.E.} + \text{Year F.E.} + \text{Country F.E.} + \varepsilon. \end{aligned} \tag{4}$$

In Eq. (4), the dependent variable *PERFPRICE* is an indicator variable that equals 1 for loans with performance pricing provisions and 0 otherwise. A significantly positive coefficient on *IFRS9* × *POST* would suggest that banks increase monitoring after IFRS 9 adoption. We

[29] In this loan-level analysis, we use OLS regression mainly because nonlinear models like probit or logit may be biased by the inclusion of various fixed effects. Nevertheless, our results are qualitatively similar when we use the probit or logit model.

follow prior literature (e.g., Kim, Song, and Stratopoulos 2018; Huang and Wang 2021) and control for a series of loan-level and borrower-level characteristics, such as loan size (*LOANSIZE*), loan maturity (*LOANMAT*), borrower size (*SIZE*), and asset tangibility (*TANGI*). We also include a series of country-level variables to control for cross-country variations in economic conditions and banking systems. All borrower- and country-level control variables are lagged by one year. Finally, we control for loan types and loan purposes, and we include industry, year, and country fixed effects.[30] We cluster standard errors at the country level.

Table 5 column (3) presents the results. Consistent with our expectation, we find a significantly positive coefficient on *IFRS9* × *POST*, suggesting that loans issued by IFRS 9–adopting banks are more likely to have performance pricing provisions in the post-adoption period. Taken together, both bank- and loan-level analyses in Table 5 support the view that banks monitor their borrowers more closely under the IFRS 9 regime. Therefore, these results corroborate the monitoring channel through which IFRS 9 adoption can enhance bank borrowers' investment-*q* sensitivity.

5.2. Heterogeneity Variation with Bank Dependence

To further shed light on the monitoring channel, we examine whether and how the impact of the switch to the ECL model under IFRS 9 on borrowers' investment-*q* sensitivity varies according to the extent of borrowers' bank dependence. We argue that when borrowers depend on banks for external financing, the economic linkage between the two increases, causing corporate borrowers' financial conditions to have a large impact on banks' overall performance. Therefore, banks closely monitor borrowers, especially those that depend on bank debt. We predict that the effect of IFRS 9 adoption on investment-*q* sensitivity will be more pronounced for bank-dependent borrowers.

[30] Country fixed effects are based on borrowers' headquarter country. Because the treatment variable, *IFRS9*, is based on lead banks' headquarter country, which can be different from borrowers' home country, the country fixed effects will not absorb *IFRS9*. Because the main effects of *POST* are absorbed by year fixed effects, it is omitted from Eq. (4).

To test this conjecture, we use both firm- and country-level measures of bank dependence. First, we use the ratio of a firm's bank debt to total assets (*BDEBTAT*) as a firm-level measure of bank dependence. We partition the treatment firms into high- or low-dependence groups based on the value of this measure in 2017, the year prior to IFRS 9 adoption. Treatment firms with a value higher than the sample median are classified as high-dependence and the rest as low-dependence. We also use two country-level measures of bank dependence: the percentage of a country's firms with non-zero bank debt (*NONZEROBD*) based on bank debt data from the Capital IQ database and the ratio of domestic bank credit to private sector to GDP (*CBKCREDIT*). By construction, higher values for these measures indicate that firms in the country are likely to depend more on bank debt. Based on the median of each country-level measure in 2017 for the 39 treatment countries/regions, we classify treatment firms in countries/regions with a value higher than the median as high (*TREAT_HIGH*) and the rest as low (*TREAT_LOW*).[31]

Table 6 presents the results using the three measures of bank dependence. In column (1), we use the firm-level bank debt ratio to partition treatment firms as high or low and find significantly positive coefficients on both three-way interaction terms. We also find that the coefficient on Q × *TREAT_HIGH* × *POST* (Coeff. = 0.0040; t-value = 3.28) is larger than that on Q × *TREAT_LOW* × *POST* (Coeff. = 0.0023; t-value = 2.44), and the difference between the two is statistically significant (p-value = 0.0266). These results are consistent with our expectation that the effect of IFRS 9 adoption on investment-q sensitivity will be more pronounced for borrowers with greater bank dependence. Using country-level measures of bank dependence in columns (2) and (3), we find consistent evidence that treatment firms in countries/regions with greater bank dependence experience a larger increase in investment-q

[31] Given that our variable of interest is already a three-way interaction term, to study the heterogeneous effect of IFRS 9 adoption, we follow Jayaraman and Wu's (2019) methodology. Specifically, we replace all *IFRS9* variables in our baseline model Eq. (2) with *TREAT_HIGH* and *TREAT_LOW* and focus on the difference in the coefficients on Q × *TREAT_HIGH* × *POST* and Q × *TREAT_LOW* × *POST*.

sensitivity after IFRS 9 adoption.[32] These results support our prediction and suggest that bank monitoring is an important channel through which IFRS 9 adoption can affect borrowers' investment-*q* sensitivity.

5.3. Heterogeneity Variation with Bank Regulation

We also examine the heterogeneity variation with bank regulation to shed light on the monitoring channel. As shown in prior studies (e.g., Christensen et al., 2013; López-Espinosa et al., 2021; and Bischof et al., 2022), regulatory enforcement is an important determinant of the effectiveness of new accounting standards. In particular, López-Espinosa et al. (2021) find that the use of ECL model increases the informativeness of loan loss provisions and this effect is stronger when regulators monitor banks more closely. We posit that banks affected by the accounting regime change will increase their monitoring of borrowers even more if they face stricter scrutiny from regulators. To the extent that the effects of this regulatory monitoring spill over to borrowers, we predict that the positive effect of the switch to the ECL model on investment-*q* sensitivity will be stronger in environments with stringent bank supervision.

To test this prediction, we use Barth, Caprio, and Levine's (2013) two country-level measures of bank regulation based on data from the Bank Regulation and Supervision Survey conducted by the World Bank. The first measure is an index of official supervisory power (*OFFICIAL*) that captures whether supervisory bodies can take action to prevent and correct problems. The second measure is an index of prompt corrective power (*CORRECTIVE*) that captures whether a law establishes predetermined levels of bank solvency deterioration that force automatic actions, such as intervention. A higher value of *OFFICIAL* or *CORRECTIVE* indicates closer supervision of banks.

[32] In Table 6 column (3), we use the 2017 value of *CBKCREDIT* to partition the treatment firms, but we continue to control for time-variant country-level bank credit supply, as captured by *CBKCREDIT*. Our inference remains unchanged if we do not control for *CBKCREDIT*.

Table 7 presents the results. Based on the median of each country-level measure in the pre-adoption period within the 39 treatment countries/regions, we split the treatment countries into groups with high or low banking regulation. In column (1), we split treatment countries based on the index of official supervisory power (*OFFICIAL*). We find that the coefficient on $Q \times TREAT\_HIGH \times POST$ (Coeff. = 0.0037; t-value = 4.63) is larger than that of $Q \times TREAT\_LOW \times POST$ (Coeff. = 0.0007; t-value = 0.60), and the difference is statistically significant (p-value = 0.0015). These results suggest that the effect of IFRS 9 adoption on investment-q sensitivity is pronounced only for treatment countries with an official supervisory power that exceeds the median level, which is consistent with our prediction. In columns (2), we split treatment countries based on the index of prompt corrective power (*CORRECTIVE*) and we find similar results. Overall, using distinct measures of banking regulation, we find consistent evidence to support our prediction that the positive effect of the switch to the ECL model on investment-q sensitivity is stronger in the presence of regulation that leads to more monitoring of banks. Our results also indicate that the monitoring effect from regulation, which spills over to banks and then to borrowers, is a mechanism through which IFRS 9 adoption impacts investment-q sensitivity.

6. Supplementary Analysis: Country-Level LLRT and Investment-*q* Sensitivity During the ICL Regime

In prior sections, we use the switch from the ICL to the ECL model as our primary setting for studying the effect of changes in bank accounting on borrowers' investment-q sensitivity. As a supplementary test, we use country-year-level LLRT to study investment-q sensitivity during the ICL regime. This analysis is based on the notion that significant country-level variation in LLRT occurs under the ICL model (Bushman and Williams 2012).[33] To

[33] Even for countries that adopted IAS 39 for loan loss accounting, regulatory treatments for loan loss provisioning varies. Some supervisory regimes, like those in Germany and Spain, explicitly promote conservative or through-the-cycle provisioning, and others like the UK's are more aligned with the evidence-based, incurred loss model,

conduct this test, we extract data from two major sources. The first is Compustat, which offers international, firm-level data for computing total investment, total q, and other control variables. The second is BankScope, which provides banks' financial data for computing LLRT measures.

To construct the country-level LLRT measures, we aggregate the bank-level measures to the country level. Our first LLRT measure (*LLRT1*) is based on the ratio of loan loss reserves in year t to non-performing loans in year t, as in Beatty and Liao (2011). Our second measure (*LLRT2*) uses non-performing loans in year t+1 to scale loan loss reserves in year t, as in Akins et al. (2017). Although these papers attempt to measure LLRT using non-performing loans as the benchmark for determining the timeliness of loan loss reserves, this approach has some limitations. Under the ICL regime, banks individually assess significant loans for specific impairment based on loan status and borrower conditions. However, for homogeneous loans that are not considered individually significant, banks primarily use statistical methods to record the reserves for these loans at inception and incremental reserves as the loans become more delinquent. Therefore, passing into non-performing loan status is not the primary trigger for recording the reserves of homogeneous loans (Ryan and Keeley 2013).[34] Given the limitations of using non-performing loans as a benchmark, our third measure (*LLRT3*) uses net charge-offs in year t+1 to benchmark loan loss reserves.[35] Specifically, we multiply −1 by the ratio of future-year net charge-offs to current-year reserves. Before aggregating, for each bank-level measure, we take the moving average in a three-year rolling window to get a stable

as prescribed by prevailing accounting principles. Moreover, supervisory enforcement actions aimed to discipline improper loan loss accounting practices can vary in both intensity and frequency across countries.

[34] The disconnect between non-performing loans and loan loss reserves is particularly salient for collateralized loans, for which loan loss reserves equal only the portion of the non-performing loans that is not covered by the collateral. In the extreme, a fully collateralized loan can be classified as non-performing and yet have zero reserves.

[35] Net charge-offs in a future year could be a better benchmark of loan loss reserves because reserves will eventually be realized and charged off. Given that net charge-offs can be 0 or negative and are usually a relatively small amount, we use the ratio of net charge-offs to loan loss reserves as an inverse measure of LLRT. For ease of interpretation, we multiply this inverse measure by −1 so that a higher value indicates timelier loan loss recognition.

measure. For the country-level aggregation, we take the weighted average of the bank-level measure for all banks in each country-year. We use banks' outstanding loans as their weights.

Next, we construct LLRT measures based on cross-sectional regressions for each country-year. Specifically, we estimate the following two models using all available bank-year observations for each country-year:

$$LLP_{i,t} = \beta_0 + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \beta_5 BANKSIZE_{i,t-1} + \beta_6 EBP_{i,t} + \beta_7 CAP_{i,t-1} + \varepsilon_{i,t}. \quad (5)$$

$$LLP_{i,t} = \beta_0 + \beta_1 \Delta NPL_{i,t-1} + \beta_2 \Delta NPL_{i,t-2} + \beta_3 BANKSIZE_{i,t-1} + \beta_4 EBP_{i,t} + \beta_5 CAP_{i,t-1} + \varepsilon_{i,t}. \quad (6)$$

In Eqs. (5) and (6), the dependent variable *LLP* is banks' loan loss provisions scaled by lagged outstanding loans. We include a series of changes in non-performing loans (ΔNPL) and banks' earnings before provisions (*EBP*), all scaled by lagged outstanding loans. *BANKSIZE* is the natural logarithm of total assets, and *CAP* represents banks' capital ratio, calculated as total equity divided by total assets. Following Bushman and Williams (2012), we define our fourth measure (*LLRT4*) as the estimated coefficient on $\Delta NPL_{i,t+1}$ from Eq. (5) for those countries with a coefficient that is statistically significant at 10 percent or higher.[36] Following Beatty and Liao (2011), we define our fifth measure (*LLRT5*) as the adjusted R^2 from Eq. (5) minus that of Eq. (6). To mitigate potential measurement errors and obtain comparable coefficients on each LLRT measure, we use the decile rank of the country-level measure divided by 10 as the measure in the regression.

In line with our sample selection procedure for the main test, we exclude financial industry firms (SIC codes 6000–6999), regulated utilities (4900–4999), and government entities (9000–9999). We also exclude firm-year observations with less than \$5 million in

[36] Requiring the coefficient to be statistically significant results in a large proportion of 0 values for *LLRT4*. Nevertheless, we find significant results with this measure. In an untabulated test, we use the coefficient as an alternative measure, without requiring it to be statistically significant, and find similar results.

physical capital or with missing or zero balances for bank debt. Our sample period covers 2001–2015 and comprises 101,619 firm-year observations from 59 countries.[37] We then run the following OLS model to examine how LLRT in the banking system is associated with borrowers' investment-q sensitivity:

$$I = \beta_0 + \beta_1 Q \times LLRT + \beta_2 Q + \beta_3 LLRT + \beta_4 SIZE + \beta_5 TANGI + \beta_6 SLACK + \beta_7 LOSS + \beta_8 ZSCORE + \beta_9 KSTR + \beta_{10} INDKSTR + \beta_{11} GDPPC + \beta_{12} INFLATION + \beta_{13} UNEMPR + \beta_{14} CBKCREDIT + \beta_{15} CBKCAPR + \beta_{16} CBKNIM + Firm\ F.E. + Year\ F.E. + \varepsilon. \tag{7}$$

In Eq. (7), the dependent variable is measured in year *t*, and all independent variables are lagged by one year. A significantly positive coefficient on $Q \times LLRT$ would suggest a positive association between LLRT in the banking system and borrowers' investment-q sensitivity. *LLRT* takes one of the five previously defined country-level measures. All other variables are defined as in our main model specification in Eq. (2). In line with our main model, we include firm and year fixed effects and cluster standard errors at the country level.

Table 8 presents the results. In column (1), consistent with classical q theory, we find a significantly positive coefficient on Q. In columns (2)–(6), we include the interaction term between Q and each country-level LLRT measure. Across these five columns, the coefficients on $Q \times LLRT$ are all positive and statistically significant, suggesting that timelier loan loss recognition in the banking system is positively associated with borrowers' investment-q sensitivity. These results complement our main finding from the difference-in-differences design, which exploits IFRS 9 adoption as a shock to LLRT.

[37] Our sample period starts with 2001 because bank debt data are available only after 2001 in Capital IQ. We end our sample period in 2015, the last available year in the Bankscope database, which we use for this supplementary test.

7. Conclusion

In this paper, we study the effect of the switch from the ICL to the ECL model in bank financial reporting on borrowers' investment-q sensitivity. Using a sample of firms from 56 countries from 2016 to 2019, we conduct difference-in-differences analyses and find that borrowers' investment-q sensitivity improves after the switch. This evidence suggests that because banks monitor their borrowers more closely after switching to the ECL model, the moral hazard problems that hinder financing of investment opportunities decrease and the relationship banking that facilitates the conversion of investment opportunities into investments increases. To further evaluate the bank monitoring channel, we conduct several analyses. In the first, we provide direct evidence for the monitoring channel: after switching to the ECL model, banks monitor their borrowers more closely, as indicated by decreased occurrence of nonperforming loans and increased use of performance pricing provisions in loan contracts. We also find that the effect of the ECL model on borrowers' investment-q sensitivity is stronger for borrowers with high bank debt dependence and for borrowers in countries with strict banking supervision. In another analysis, we directly measure LLRT in each country's banking system and show that under the ICL regime, timelier loan loss recognition is associated with higher borrower investment-q sensitivity.

Overall, our study offers the novel insight that the reporting system used by one contracting party (i.e., the lender) can have real effects on the other contracting party (i.e., the borrower). In doing so, it extends the research on the consequences of financial reporting in banks' role as delegated monitors of borrowers. It highlights that when banks are more active in the role as delegated monitors, there is a positive impact on borrowers. It also provides a further understanding of the costs and benefits of the switch from the ICL to the ECL model, a switch that has been regarded as a major change in bank accounting. In particular, we document a possibly unintended benefit: improvement in borrowers' investment efficiency.

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Appendix A. Variable definitions

Variable (in alphabetical order)	Definition
BDEBTAT	A firm-level measure of bank dependence, calculated as bank debt balance divided by total assets. Sources: Compustat and Capital IQ.
BKCAPR	Bank's capital ratio in year $t-1$, calculated as total equity divided by total assets. Source: BankFocus.
BKNIM	Bank's net interest margin in year t-1, calculated as net interest income divided by average total assets. Source: BankFocus.
BKROE	Bank's return on equity in year $t-1$, calculated as net income divided by average total equity. Source: BankFocus.
BKSIZE	Bank size in year $t-1$, measured as the natural logarithm of the bank's total assets in USD millions. Source: BankFocus.
CBKCAPR	Country-level measure of bank capital ratio in year t-1. To construct this measure, we first calculate bank-level capital ratio as total equity divided by total assets. We then take the weighted average of the bank-level capital ratio within each country-year and use bank's total assets as the weight. Source: BankFocus.
CBKCREDIT	Country-level measure of bank credit in year t-1, calculated as the ratio of domestic bank credit to private sector to GDP. Source: World Bank.
CBKNIM	Country-level measure of bank net interest margin in year t-1. To construct this measure, we first calculate bank-level net interest margin as net interest income divided by average total assets. We then take the weighted average of the bank-level net interest margin within each country-year and use bank's total assets as the weight. Source: BankFocus.
CFOVOL	Cash flow volatility during the past five years, calculated as the standard deviation of annual cash flow from operations (*oancf*) divided by lagged total assets (*at*) from years $t-5$ to $t-1$.
CORRECTIVE	A country-level index of banking regulators' prompt corrective power, which captures whether a law establishes predetermined levels of bank solvency deterioration for forcing automatic actions, such as intervention. A higher value for this index indicates a quicker response to bank problems. To construct the index, Barth et al. (2013) aggregate answers to the following survey questions: (1) Does the supervisory agency operate an early intervention framework (e.g., prompt corrective action) that forces automatic action when certain regulatory triggers or thresholds are breached? (2) Please indicate whether the following enforcement powers are available to the supervisory agency: Cease-and-desist-type orders for imprudent bank practices; Banks required to constitute provisions to cover actual or potential losses; Banks required to reduce or suspend dividends to shareholders; Banks required to reduce or suspend bonuses and other remuneration to bank directors and managers. (3) Can the supervisory authority force a bank to change its internal organizational structure? Source: Bank Regulation and Supervision Survey conducted by the World Bank.
DEBTSTR	Firm's debt structure in year $t-1$, defined as the balance of bank debt divided by the balance of total debt. Source: Capital IQ.
EBITDA	Firm performance in year $t-1$, measured as earnings before interest, taxes, depreciation, and amortization (*ebitda*) divided by lagged total assets (*at*).
GDPPC	Natural logarithm of country-level GDP per capita (constant 2010 USD) in year $t-1$. Source: World Bank.

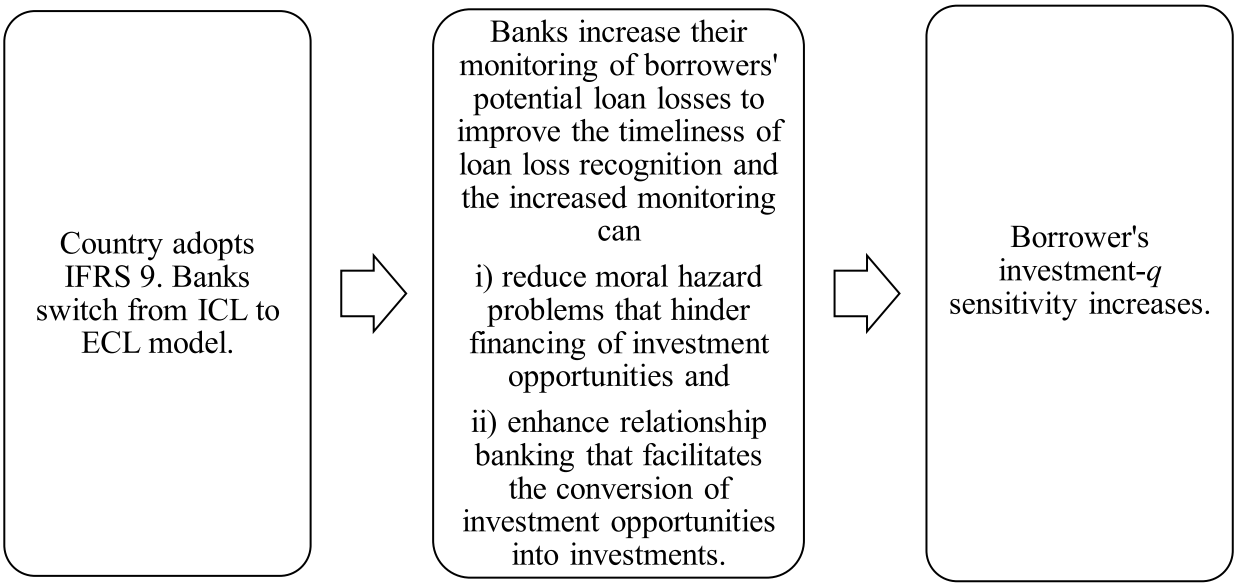
I	Firm's total investment in year *t*, calculated as the sum of physical and intangible investment divided by the lagged total replacement costs of physical and intangible capital. Following Peters and Taylor (2017), we measure physical investment as capital expenditure (*capx*) and intangible investment as R&D expenditure (*xrd*) plus 30% of SG&A expenses (*xsga* minus *xrd*). We measure the replacement costs of physical capital as the gross value of property, plant, and equipment (*ppegt*). The replacement costs of intangible capital include two components: (i) a firm's externally purchased intangible capital, as reflected in the balance sheet account of intangible assets (*intan*) and (ii) internally created intangible capital derived from a perpetual inventory method (as described in Section III, Investment and the Tobin's *q* Measure) and based on the firm's past records of R&D and SG&A spending.
IFRS9	Indicator variable that equals 1 for countries that adopted IFRS 9 on January 1, 2018, and 0 otherwise. Source: Hand-collected by authors.
INDKSTR	Industry-level capital structure in year *t*−1, calculated as the mean of *KSTR* for firms in the same SIC 3-digit industry, country, and year.
INFLATION	Country-level annual inflation rate in year *t*-1. Source: World Bank.
KSTR	Firm's capital structure in year *t*−1, measured as long-term debt (*dltt*) divided by the sum of long-term debt and the market value of equity (*prcc_f* times *csho* for firms in the Compustat North American database and *prccd* of a firm's primary issue times *cshoi* for firms in the Compustat Global database).
LEV	Financial leverage in year *t*−1, calculated as total debt (*dltt* + *dlc*) divided by total assets (*at*).
LLRT1	Our first country-level measure of loan loss recognition timeliness. We first construct a bank-level measure using the ratio of loan loss reserves in year *t* to non-performing loans in year *t*, as used in Beatty and Liao (2011). To derive a more stable measure, we take the moving average of the ratio in a three-year rolling window. To aggregate the bank-level measure to the country level, we use banks' outstanding loans as their weights and take the weighted average of the bank-level measure for all banks in each country-year. We use the decile rank of the country-level measure divided by 10 as our measure for conducting the empirical analyses. Source: BankScope.
LLRT2	Our second country-level measure of loan loss recognition timeliness. We first construct a bank-level measure as the ratio of loan loss reserves in year *t* to non-performing loans in year *t*+1, introduced by Akins et al. (2017). To derive a more stable measure, we then take the moving average of the ratio in a three-year rolling window. To aggregate the bank-level measure to the country level, we use banks' outstanding loans as their weights and take the weighted average of the bank-level measure for all banks in each country-year. We use the decile rank of the country-level measure divided by 10 as our measure for conducting the empirical analyses. Source: BankScope.
LLRT3	Our third country-level measure of loan loss recognition timeliness. We first construct a bank-level measure as the ratio of net charge-offs in year *t*+1 to loan loss reserves in year *t*, multiplied by −1. To derive a more stable measure, we then take the moving average of the ratio in a three-year rolling window. To aggregate the bank-level measure to the country level, we use banks' outstanding loans as their weights and take the weighted average of the bank-level measure for all banks in each country-year. We use the decile rank of the country-level measure divided by 10 as our measure for conducting the empirical analyses. Source: BankScope.
LLRT4	This variable equals the coefficient on $\Delta NPL_{i,t+1}$ from the following regression model for countries with a coefficient that is statistically significant at the 10% level or higher and equals 0 for other countries. Following Bushman and Williams (2012), we estimate the following model separately for each country-year using all available banks:

	$LLP_{i,t} = \beta_0 + \beta_1\Delta NPL_{i,t+1} + \beta_2\Delta NPL_{i,t} + \beta_3\Delta NPL_{i,t-1} + \beta_4\Delta NPL_{i,t-2} + \beta_5 BANKSIZE_{i,t-1} + \beta_6 EBP_{i,t} + \beta_7 CAP_{i,t-1} + \varepsilon_{i,t}$. The dependent variable is banks' loan loss provisions (*LLP*), the independent variables include a series of changes in non-performing loans (ΔNPL) and earnings before provisions (*EBP*), and all are scaled by lagged outstanding loans. The model also controls for bank size (*BANKSIZE*), measured as the natural logarithm of total assets, and capital ratio (*CAP*), calculated as total equity divided by total assets. We use the decile rank of the country-level measure divided by 10 as our measure for conducting empirical analyses. Source: BankScope.
LLRT5	The difference in adjusted R^2 from two regression models of loan loss provisions. The simpler model is as follows: $LLP_{i,t} = \beta_0 + \beta_1\Delta NPL_{i,t-1} + \beta_2\Delta NPL_{i,t-2} + \beta_3 BANKSIZE_{i,t-1} + \beta_4 EBP_{i,t} + \beta_5 CAP_{i,t-1} + \varepsilon_{i,t}$. The longer model is the same as that used to construct *LLRT4*, with changes in non-performing loans (ΔNPL) in years *t* and *t*+1 as additional explanatory variables. Following Beatty and Liao (2011), we estimate both models separately for each country-year using all available banks and subtract the adjusted R^2 of the longer model from that of the simpler model. We use the decile rank of the country-level measure divided by 10 as our measure for conducting empirical analyses. Source: Bankscope.
LOANMAT	Natural logarithm of the loan facility's maturity in months. Source: DealScan.
LOANSIZE	Natural logarithm of the loan amount of the facility in USD millions. Source: DealScan.
LOSS	An indicator variable that equals 1 if the firm's income before extraordinary items (*ib*) is negative and 0 otherwise.
NONZEROBD	A country-level measure of bank dependence, calculated as the percentage of a country's firms with non-zero bank debt. Sources: Compustat and Capital IQ.
NPL1	Bank's nonperforming loans in year *t* scaled by total outstanding loans. Source: BankFocus.
NPL2	Bank's nonperforming loans in year *t* scaled by total assets. Source: BankFocus.
OFFICIAL	A country-level index of banking regulators' official supervisory power capturing whether supervisory authorities can take actions to prevent and correct problems. A higher value indicates greater supervisory power. To construct the index, Barth et al. (2013) aggregate answers to the following survey questions: (1) Does the banking supervisor have the right to meet with the external auditors and discuss their report without the approval of the bank? (2) Are auditors required to communicate directly to the supervisory agency any presumed involvement of bank directors or senior managers in illicit activities, fraud, or insider abuse? (3) In cases where the supervisor identifies that the bank has received an inadequate audit, does the supervisor have the power to take actions against the external auditor? (4) Can the supervisory authority force a bank to change its internal organizational structure? (5) Do banks disclose off-balance-sheet items to the supervisors? (6) Please indicate whether the following enforcement powers are available to the supervisory agency: Banks required to constitute provisions to cover actual or potential losses; Banks required to reduce or suspend dividends to shareholders; Banks required to reduce or suspend bonuses and other remuneration to bank directors and managers. (7) Can the bank supervisor, deposit insurance agency, or bank restructuring or asset management agency perform the following problem bank resolution activities: Declare insolvency; Supersede shareholders' rights; Remove and replace bank senior management and directors. Source: Bank Regulation and Supervision Survey conducted by the World Bank.
PERFPRICE	An indicator that equals 1 for loan facilities with performance pricing provisions and 0 otherwise. Source: DealScan.
POST	Indicator variable that equals 1 for years 2018 and 2019 and 0 for years 2016 and 2017.

Q	Total *q* in year *t*−1, calculated as a firm's market value divided by the total replacement costs of physical and intangible capital. We calculate a firm's market value as the market value of its outstanding equity (*prcc_f* times *csho* for firms in the Compustat North American database and *prccd* of a firm's primary issue times *cshoi* for firms in the Compustat Global database), plus the book value of its total debt (*dltt* plus *dlc*), minus its current assets (*act*). We measure the replacement costs of physical capital as the gross value of property, plant, and equipment. The replacement costs of intangible capital include two components: (i) a firm's externally purchased intangible capital, as reflected in the balance sheet account of intangible assets (*intan*) and (ii) internally created intangible capital derived from a perpetual inventory method (as described in Section III, Investment and the Tobin's *q* Measure) and based on the firm's past records of R&D and SG&A spending.
SIZE	Firm size in year *t*−1, measured as the natural logarithm of the firm's total assets (*at*) in USD millions.
SLACK	Firm's financial slack in year *t*−1, measured as the ratio of cash and short-term investment (*che*) to the net value of property, plant, and equipment (*ppent*).
T2017	Indicator variable that equals 1 for observations in 2017 and 0 otherwise.
T2018	Indicator variable that equals 1 for observations in 2018 and 0 otherwise.
T2019	Indicator variable that equals 1 for observations in 2019 and 0 otherwise.
TANGI	Firm's asset tangibility in year *t*−1, calculated as the net value of property, plant, and equipment (*ppent*) divided by total assets (*at*).
TREAT_HIGH	We split our treatment firms into two groups, high vs. low, based on various partitioning variables in our analyses. *TREAT_HIGH* equals 1 for treatment firms with a partitioning variable value that exceeds the median and 0 otherwise.
TREAT_LOW	We split our treatment firms into two groups, high vs. low, based on various partitioning variables in our analyses. *TREAT_LOW* equals 1 for treatment firms with a partitioning variable value less than or equal to the median and 0 otherwise.
UNEMPR	Country-level unemployment rate in year *t*-1. Source: World Bank.
ZSCORE	Firm's Altman's (1968) Z-score in year *t*−1, calculated as (1.2 × working capital + 1.4 × retained earnings + 3.3 × earnings before interest and taxes + 0.999 × sales) / total assets + 0.6 × market value of equity / book value of debt.

This appendix provides definitions of the variables used in our analyses. Sources are Compustat North America and Compustat Global (our primary data sources) unless otherwise noted.

Figure 1: How the switch from the incurred credit loss (ICL) to the expected credit loss (ECL) model can affect firms' investment-*q* sensitivity



ECL: expected credit loss; ICL: incurred credit loss;

IFRS: International Financial Reporting Standards.

Table 1. Sample distribution

Panel A: Sample distribution by country

Country/region	*N*	*IFRS9*	Country/region	*N*	*IFRS9*
Argentina	86	0	Kuwait	161	1
Australia	1,225	1	Luxembourg	94	1
Austria	134	1	Malaysia	1,850	1
Bangladesh	341	0	Mexico	269	0
Belgium	186	1	Netherlands	222	1
Brazil	520	0	New Zealand	179	1
Bulgaria	57	1	Nigeria	173	1
Canada	1,438	1	Norway	295	1
Chile	295	0	Pakistan	742	0
China	9,190	1	Peru	165	0
Colombia	68	0	Philippines	327	1
Croatia	178	1	Poland	596	1
Cyprus	80	1	Portugal	114	1
Denmark	209	1	Russian Federation	283	0
Egypt	207	0	Saudi Arabia	330	1
Finland	254	1	Singapore	1,060	1
France	1,039	1	South Africa	417	1
Germany	889	1	Spain	304	1
Greece	302	1	Sri Lanka	465	1
Hong Kong, China	2,089	1	Sweden	509	1
India	4,730	0	Switzerland	399	1
Indonesia	1,069	0	Taiwan, China	4,389	1
Ireland	129	1	Thailand	1,274	0
Israel	494	0	Turkey	665	1
Italy	443	1	United Arab Emirates	133	1
Japan	8,214	0	United Kingdom	1,592	1
Jordan	197	1	United States	5,140	0
Korea, Rep.	2,483	1	Vietnam	386	0
			Total	59,079	

Panel B: Sample distribution by year

Year	*IFRS9* = 0	*IFRS9* = 1	*N*	%
2016	6,103	8,667	14,770	25.00
2017	6,229	8,897	15,126	25.60
2018	6,076	8,766	14,842	25.12
2019	5,875	8,466	14,341	24.27
Total	24,283	34,796	59,079	100.00

This table presents the distribution of our final sample. Panel A presents the sample distribution by country/region for our main analysis examining the effect of IFRS 9 adoption on borrowers' investment-*q* sensitivity from 2016–2019. Panel B presents the sample distribution separately by year for the treatment (*IFRS9* = 1) and control (*IFRS9* = 0) groups. *IFRS9* is an indicator variable that equals 1 for countries that adopted IFRS 9 on January 1, 2018, and 0 otherwise.

Table 2. Descriptive statistics (*N* = 59,079)

Variable	Mean	S.D.	25%	Median	75%
I	0.126	0.099	0.063	0.103	0.157
Q	1.145	2.065	0.162	0.549	1.291
IFRS9	0.589	0.492	0.000	1.000	1.000
POST	0.494	0.500	0.000	0.000	1.000
SIZE	6.068	1.747	4.807	5.937	7.201
TANGI	0.329	0.219	0.154	0.288	0.467
SLACK	1.115	2.224	0.126	0.389	1.054
LOSS	0.212	0.409	0.000	0.000	0.000
ZSCORE	3.160	3.380	1.453	2.452	3.864
KSTR	0.463	0.383	0.073	0.399	0.887
INDKSTR	0.405	0.278	0.160	0.357	0.642
GDPPC	9.768	1.155	8.902	10.160	10.790
INFLATION	0.020	0.020	0.007	0.017	0.032
UNEMPR	0.049	0.030	0.034	0.043	0.053
CBKCREDIT	1.004	0.462	0.544	1.042	1.348
CBKCAPR	0.079	0.024	0.064	0.072	0.085
CBKNIM	0.023	0.013	0.013	0.019	0.028

This table presents the summary statistics for the regression variables used in our main analysis examining the effect of IFRS 9 adoption on borrowers' investment-*q* sensitivity. Our sample period covers 2016–2019. Our final sample comprises 59,079 firm-year observations from 56 countries/regions. Appendix A summarizes all variable definitions.

Table 3. Effect of the switch to the expected credit loss model on investment-*q* sensitivity

Dep. Var. = *I*	(1)	(2)
Q × IFRS9 × POST	0.0030***	
	(3.09)	
Q × IFRS9 × T2017		0.0014
		(0.98)
Q × IFRS9 × T2018		0.0029**
		(2.26)
Q × IFRS9 × T2019		0.0058***
		(2.70)
Q	0.0101***	0.0096***
	(5.58)	(4.13)
IFRS9 × POST	-0.0062***	
	(-2.79)	
Q × IFRS9	-0.0038*	-0.0039
	(-1.91)	(-1.65)
Q × POST	-0.0017**	
	(-2.22)	
SIZE	-0.0540***	-0.0546***
	(-8.34)	(-8.23)
TANGI	-0.2613***	-0.2608***
	(-14.53)	(-14.51)
SLACK	0.0051***	0.0051***
	(6.53)	(6.59)
LOSS	-0.0070***	-0.0070***
	(-5.47)	(-5.53)
ZSCORE	0.0025**	0.0025**
	(2.51)	(2.61)
KSTR	-0.0196***	-0.0193***
	(-5.83)	(-5.76)
INDKSTR	-0.0002	-0.0007
	(-0.02)	(-0.11)
GDPPC	0.0051	0.0078
	(0.20)	(0.34)
INFLATION	-0.0483	-0.0763*
	(-1.15)	(-1.77)
UNEMPR	-0.4922***	-0.4440***
	(-5.85)	(-5.90)
CBKCREDIT	0.0135	-0.0007
	(0.55)	(-0.03)
CBKCAPR	0.4933***	0.3769***
	(3.92)	(3.18)
CBKNIM	-0.7024***	-0.4899**
	(-2.90)	(-2.52)
IFRS9 × T2017		0.0068***
		(2.97)
IFRS9 × T2018		-0.0011
		(-0.40)
IFRS9 × T2019		-0.0026
		(-0.70)
Q × T2017		0.0012
		(0.89)
Q × T2018		-0.0008
		(-0.76)
Q × T2019		-0.0013
		(-0.68)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	59,079	59,079
Adj. R^2	0.668	0.669

This table presents our results of the tests of the effect of the switch to the expected credit loss (ECL) model on investment-q sensitivity. Specifically, we use a difference-in-differences design to study the effect of the switch to the ECL model under IFRS 9 on borrowers' investment-q sensitivity from 2016–2019. The dependent variable I is the firm's total investment in year t, including physical and intangible investment, scaled by the lagged total replacement costs of physical and intangible capital. We focus on the three-way interaction term $Q \times IFRS9 \times POST$. Q is the firm's total q in year $t-1$, calculated as its market value divided by the total replacement costs of physical and intangible capital. *IFRS9* is an indicator variable that equals 1 for countries that adopted IFRS 9 on January 1, 2018, and 0 otherwise. *POST* is an indicator variable that equals 1 for 2018 and 2019 and 0 for 2016 and 2017. All control variables are measured in year $t-1$. Appendix A summarizes all variable definitions. The t values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms are estimated but omitted for brevity. ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 4. Robustness checks

Panel A: Alternative sample

Dep. Var. = I	(1) Excluding fiscal year 2018	(2) Excluding fiscal years 2016 and 2018	(3) Including firms with physical assets less than \$5 million	(4) Falsification test assuming 2016 as the year of adoption	(5) Falsification test assuming 2014 as the year of adoption
Q × IFRS9 × POST	0.0047***	0.0045***	0.0028**	-0.0020	0.0007
	(3.20)	(3.45)	(2.49)	(-1.26)	(0.54)
Q	0.0101***	0.0136***	0.0101***	0.0092***	0.0096**
	(5.07)	(5.88)	(5.67)	(3.51)	(2.33)
IFRS9 × POST	-0.0065**	-0.0106***	-0.0060**	-0.0055	-0.0008
	(-2.01)	(-3.85)	(-2.19)	(-1.37)	(-0.17)
Q × IFRS9	-0.0036*	-0.0047*	-0.0028	-0.0009	0.0030
	(-1.71)	(-1.87)	(-1.42)	(-0.33)	(0.74)
Q × POST	-0.0020	-0.0022**	-0.0023***	-0.0018	-0.0012
	(-1.55)	(-2.26)	(-3.17)	(-1.61)	(-1.10)
Control variables	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	44,077	28,228	69,859	58,336	53,768
Adj. R^2	0.645	0.625	0.655	0.645	0.647

Panel B: Alternative model specification

Dep. Var. = I	(1) Including country × year fixed effects	(2) Weighted least squares regression	(3) Propensity scores matched sample	(4) Controlling for debt structure's effect on investment-q sensitivity
Q × IFRS9 × POST	0.0027**	0.0028***	0.0030***	0.0026**
	(2.04)	(3.38)	(2.84)	(2.44)
Q	0.0099***	0.0098***	0.0109***	0.0095***
	(5.31)	(7.70)	(5.81)	(4.82)
IFRS9 × POST		-0.0056***	-0.0052**	-0.0061***
		(-4.85)	(-2.48)	(-2.98)
Q × IFRS9	-0.0029	-0.0035***	-0.0052**	-0.0031*
	(-1.37)	(-2.70)	(-2.04)	(-1.82)
Q × POST	-0.0015	-0.0015**	-0.0018**	-0.0016*
	(-1.47)	(-2.40)	(-2.57)	(-1.80)
DEBTSTR				-0.0011
				(-0.27)
DEBTSTR × Q				-0.0004
				(-0.27)
Control variables	Yes	Yes	Yes	Yes
Country × Year FE	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
N	59,079	59,079	47,422	56,766
Adj. R^2	0.670	0.668	0.663	0.673

Table 4. - Cont'd.

Panel C: Evaluating omitted variable concern

	Coefficient on $Q \times IFRS9 \times POST$	R^2
Model without controls and fixed effects	0.0043	0.123
Model with controls and fixed effects	0.0030	0.755
Outputs from the Oster (2019) test:		
The maximum R^2	0.981	
δ	2.781	
Is the bias-adjusted coefficient within original confidence interval?	Yes	
Bias-adjusted coefficient on $Q \times IFRS9 \times POST$	0.0023	

This table presents our robustness checks. In Panel A, we check whether our results are sensitive to alternative samples and conduct a falsification test in the last two columns. In Panel B, we present results from using various alternative model specifications. In Panel C, we conduct the Oster (2019) test to evaluate the sensitivity of our main results to unobservable selection and coefficient stability. Appendix A summarizes all variable definitions. The t values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Control variables (same as in our baseline model) and constant terms are estimated but omitted for brevity. ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 5. Test of monitoring channel

	Bank-level analysis: Bank's nonperforming loans after IFRS 9 adoption		Loan-level analysis: Loan contracting term after IFRS 9 adoption	
	(1)	(2)		(3)
Dep. Var. =	*NPL1*	*NPL2*		*PERFPRICE*
IFRS9 × POST	-0.0092**	-0.0044**	*IFRS9 × POST*	0.0320***
	(-2.02)	(-2.44)		(3.61)
BKSIZE	-0.0030	0.0000	*IFRS9*	-0.0062
	(-0.83)	(0.03)		(-0.76)
BKCAPR	-0.0229	-0.0113	*LOANSIZE*	0.0151**
	(-1.05)	(-0.94)		(2.09)
BKROE	-0.0398***	-0.0216***	*LOANMAT*	-0.0110*
	(-3.30)	(-3.16)		(-1.92)
BKNIM	0.0491*	0.0108	*SIZE*	0.0093**
	(1.89)	(0.74)		(2.18)
GDPPC	0.0422	0.0340	*TANGI*	-0.0030
	(0.77)	(1.25)		(-0.23)
INFLATION	0.1397	0.0645*	*LEV*	-0.0585**
	(1.58)	(1.68)		(-2.11)
UNEMPR	0.4707**	0.2284**	*ZSCORE*	-0.0002
	(2.31)	(2.31)		(-0.18)
CBKCREDIT	0.1518*	0.0811**	*EBITDA*	0.1622**
	(1.73)	(2.21)		(2.17)
CBKCAPR	0.0584	0.0366	*CFOVOL*	-0.0859
	(0.43)	(0.60)		(-1.31)
CBKNIM	0.0337	0.0158	*GDPPC*	-0.5689
	(0.18)	(0.20)		(-0.86)
			INFLATION	-0.9314
				(-1.41)
			UNEMPR	1.6942
				(1.16)
			CBKCREDIT	-0.2976
				(-1.12)
			CBKCAPR	-1.3734
				(-0.50)
			CBKNIM	8.7424*
				(1.70)
			Loan type FE	Yes
			Loan purpose FE	Yes
			Industry FE	Yes
Bank FE	Yes	Yes	Country FE	Yes
Year FE	Yes	Yes	Year FE	Yes
N	49,402	49,402		9,932
adj. R^2	0.818	0.830		0.116

This table presents the results of testing the monitoring channel. In columns (1) and (2), we conduct bank-level analyses to examine the effect of IFRS 9 adoption on bank's nonperforming loans. Our final sample for this test consists of 49,402 bank-year observations from 2016–2019. In this test, *IFRS9* is an indicator variable that equals 1 for banks in an IFRS 9-adopting country and 0 otherwise. The dependent variables, *NPL1* and *NPL2*, are banks' nonperforming loans in year *t* scaled by total loans and total assets, respectively. In column (3), we conduct a loan-level analysis to examine the effect of IFRS 9 adoption on bank monitoring, as indicated by loan contracting term. Our sample for this test consists of 9,932 loan facilities issued from 2016–2019. In this test, *IFRS9* is an indicator variable that equals 1 for loans with at least one lead bank headquartered in an IFRS 9-adopting country and 0 otherwise. The dependent variable (*PERFPRICE*) is an indicator that equals 1 for loan facilities with a performance pricing provision and 0 otherwise. We include industry, year, and country fixed effects in this linear probability model. All control variables are measured in year $t-1$. Appendix A summarizes all variable definitions. The *t* values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms are estimated but omitted for brevity. ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 6. Heterogeneity variation with bank dependence

Dep. Var. = *I* Firm-level or country-level variable used to partition the treatment firms into high vs. low group:	(1) Firm-level ratio of bank debt to total assets (*BDEBTAT*)	(2) Percentage of a country's firms with non-zero bank debt (*NONZEROBD*)	(3) Ratio of domestic bank credit to private sector to GDP (*CBKCREDIT*)
Q × *TREAT_HIGH* × *POST* [A]	0.0040***	0.0033***	0.0032***
	(3.28)	(3.29)	(3.36)
Q × *TREAT_LOW* × *POST* [B]	0.0023**	0.0012	0.0009
	(2.44)	(0.97)	(0.66)
Q	0.0101***	0.0101***	0.0101***
	(5.58)	(5.56)	(5.59)
TREAT_HIGH × *POST*	-0.0107***	-0.0078***	-0.0064***
	(-4.65)	(-3.40)	(-2.74)
TREAT_LOW × *POST*	-0.0017	-0.0028	-0.0048**
	(-0.68)	(-1.11)	(-2.19)
Q × *TREAT_HIGH*	-0.0035	-0.0049**	-0.0042**
	(-1.62)	(-2.65)	(-2.18)
Q × *TREAT_LOW*	-0.0038*	0.0016	0.0010
	(-1.93)	(0.54)	(0.44)
Q × *POST*	-0.0017**	-0.0017**	-0.0017**
	(-2.24)	(-2.27)	(-2.20)
SIZE	-0.0540***	-0.0538***	-0.0541***
	(-8.35)	(-8.32)	(-8.39)
TANGI	-0.2611***	-0.2592***	-0.2606***
	(-14.53)	(-14.17)	(-14.81)
SLACK	0.0051***	0.0050***	0.0051***
	(6.57)	(6.42)	(6.48)
LOSS	-0.0070***	-0.0070***	-0.0070***
	(-5.47)	(-5.52)	(-5.42)
ZSCORE	0.0025**	0.0025**	0.0024**
	(2.61)	(2.51)	(2.51)
KSTR	-0.0189***	-0.0194***	-0.0194***
	(-5.71)	(-5.78)	(-5.80)
INDKSTR	0.0000	0.0001	0.0002
	(0.01)	(0.02)	(0.04)
GDPPC	0.0089	0.0028	0.0008
	(0.34)	(0.10)	(0.03)
INFLATION	-0.0440	-0.0545	-0.0501
	(-1.05)	(-1.32)	(-1.22)
UNEMPR	-0.4822***	-0.4845***	-0.4903***
	(-5.77)	(-5.99)	(-5.78)
CBKCREDIT	0.0127	0.0111	0.0124
	(0.52)	(0.45)	(0.51)
CBKCAPR	0.4836***	0.4807***	0.4934***
	(3.84)	(3.81)	(3.96)
CBKNIM	-0.7031***	-0.6715***	-0.6849***
	(-2.90)	(-2.70)	(-2.84)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	59,079	59,079	59,079
Adj. R^2	0.669	0.669	0.668
p-value of testing the difference in coefficients on [A] and [B]:	0.0266**	0.0634*	0.0979*

This table presents the analysis of heterogeneity variation with bank dependence. We partition our treatment firms into two groups, high and low, based on three measures of bank dependence, and test the difference in coefficients between the two three-way interaction terms. *TREAT_HIGH* (*TREAT_LOW*) is an indicator of the high (low) group of treatment firms: it equals 1 for treatment firms with a partitioning variable value that is greater than (less than or equal to) the median and 0 otherwise. In column (1), we use a firm-level measure of bank dependence (*BDEBTAT*), defined as the ratio of bank debt to total assets. In columns (2) and (3), we use country-level measures *NONZEROBD* and *CBKCREDIT*, respectively. *NONZEROBD* is the percentage of a country's firms with non-zero bank debt. *CBKCREDIT* is the ratio of domestic bank credit to private sector to GDP. Appendix A summarizes all variable definitions. The *t* values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms are estimated but omitted for brevity. ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 7. Heterogeneity variation with bank regulation

Dep. Var. = *I* Country-level variable used to partition the treatment firms into high vs. low groups:	(1) Official supervisory power (*OFFICIAL*)	(2) Prompt corrective power (*CORRECTIVE*)
Q × *TREAT_HIGH* × *POST* [A]	0.0037***	0.0032***
	(4.63)	(3.43)
Q × *TREAT_LOW* × *POST* [B]	0.0007	0.0008
	(0.60)	(0.55)
Q	0.0101***	0.0102***
	(5.57)	(5.65)
TREAT_HIGH × *POST*	-0.0076***	-0.0076***
	(-3.12)	(-3.03)
TREAT_LOW × *POST*	-0.0036	-0.0030
	(-1.60)	(-1.34)
Q × *TREAT_HIGH*	-0.0048**	-0.0048**
	(-2.62)	(-2.58)
Q × *TREAT_LOW*	0.0005	0.0026
	(0.20)	(0.91)
Q × *POST*	-0.0017**	-0.0017**
	(-2.24)	(-2.25)
SIZE	-0.0539***	-0.0540***
	(-8.34)	(-8.36)
TANGI	-0.2591***	-0.2592***
	(-14.17)	(-14.24)
SLACK	0.0050***	0.0050***
	(6.36)	(6.44)
LOSS	-0.0070***	-0.0071***
	(-5.51)	(-5.53)
ZSCORE	0.0025**	0.0024**
	(2.53)	(2.49)
KSTR	-0.0193***	-0.0195***
	(-5.76)	(-5.84)
INDKSTR	0.0001	0.0005
	(0.01)	(0.07)
GDPPC	-0.0013	0.0023
	(-0.05)	(0.08)
INFLATION	-0.0552	-0.0508
	(-1.29)	(-1.18)
UNEMPR	-0.4874***	-0.4833***
	(-6.13)	(-6.00)
CBKCREDIT	0.0139	0.0128
	(0.58)	(0.52)
CBKCAPR	0.4742***	0.4731***
	(3.72)	(3.75)
CBKNIM	-0.6656***	-0.6750***
	(-2.70)	(-2.79)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	59,079	59,079
Adj. R^2	0.669	0.669
p-value of testing the difference in coefficients on [A] and [B]:	0.0015***	0.0639*

This table presents the analysis of the heterogeneity variation with bank regulation. We partition our treatment firms into two groups, high and low, based on two country-level measures of bank regulation, and test the difference in coefficients between the two three-way interaction terms. *TREAT_HIGH* (*TREAT_LOW*) is an indicator of the high (low) group of treatment firms: it equals 1 for treatment firms with a partitioning variable value that is greater than (less than or equal to) the median and 0 otherwise. In columns (1) and (2), we respectively use an index of bank regulators' official supervisory power (*OFFICIAL*) and prompt corrective power (*CORRECTIVE*). Appendix A summarizes all variable definitions. The *t* values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms are estimated but omitted for brevity. ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 8. Association between country-level loan loss recognition timeliness (LLRT) and investment-*q* sensitivity during the incurred credit loss (ICL) regime

Dep. Var. = *I*	(1)	(2)	(3)	(4)	(5)	(6)
LLRT measure =	*LLRT1*	*LLRT1*	*LLRT2*	*LLRT3*	*LLRT4*	*LLRT5*
Q × LLRT		0.0098***	0.0077**	0.0124***	0.0134***	0.0118***
		(3.28)	(2.27)	(4.71)	(4.15)	(10.13)
Q	0.0088***	0.0022	0.0049**	0.0042	0.0067***	0.0042**
	(6.48)	(0.73)	(2.11)	(1.50)	(3.38)	(2.48)
LLRT	0.0180	0.0136	-0.0024	0.0109	-0.0090***	0.0021
	(1.45)	(1.14)	(-0.12)	(1.21)	(-2.87)	(0.36)
SIZE	-0.0260***	-0.0255***	-0.0279***	-0.0268***	-0.0255***	-0.0261***
	(-5.13)	(-5.04)	(-4.98)	(-4.89)	(-4.66)	(-4.61)
TANGI	-0.1845***	-0.1831***	-0.1989***	-0.1956***	-0.1925***	-0.1940***
	(-7.60)	(-7.66)	(-6.84)	(-6.54)	(-5.84)	(-5.77)
SLACK	0.0074**	0.0073**	0.0072**	0.0071**	0.0076**	0.0076**
	(2.62)	(2.62)	(2.49)	(2.50)	(2.49)	(2.47)
LOSS	-0.0145***	-0.0145***	-0.0129***	-0.0127***	-0.0133***	-0.0131***
	(-3.76)	(-3.76)	(-3.52)	(-3.57)	(-3.27)	(-3.33)
ZSCORE	0.0057***	0.0056***	0.0055***	0.0057***	0.0053***	0.0054***
	(8.46)	(8.89)	(11.04)	(9.26)	(9.74)	(8.67)
KSTR	-0.0175***	-0.0178***	-0.0187***	-0.0190***	-0.0181**	-0.0179**
	(-2.76)	(-2.87)	(-2.81)	(-2.71)	(-2.57)	(-2.49)
INDKSTR	0.0022	0.0012	0.0007	0.0032	0.0066	0.0058
	(0.26)	(0.15)	(0.08)	(0.41)	(0.78)	(0.74)
GDPPC	-0.0294	-0.0315	0.0254	0.0243	0.0201	0.0055
	(-0.72)	(-0.82)	(0.58)	(0.74)	(0.46)	(0.14)
INFLATION	0.1951***	0.1942***	0.1942***	0.1752***	0.1943***	0.2196***
	(4.11)	(4.13)	(5.41)	(3.89)	(4.53)	(4.45)
UNEMPR	-0.1573**	-0.1511*	-0.0569	-0.0450	-0.1454**	-0.1484**
	(-2.04)	(-2.00)	(-0.85)	(-0.77)	(-2.09)	(-2.28)
CBKCREDIT	-0.0083	-0.0116	-0.0033	-0.0056	-0.0043	-0.0071
	(-0.49)	(-0.67)	(-0.21)	(-0.37)	(-0.22)	(-0.45)
CBKCAPR	-0.0554	-0.0565	0.0410	0.0594	0.0728	0.0765
	(-0.54)	(-0.56)	(0.41)	(0.56)	(0.45)	(0.48)
CBKNIM	0.1147	0.1186	0.0664	0.0123	0.0743	0.0263
	(0.62)	(0.65)	(0.39)	(0.07)	(0.44)	(0.15)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	101,619	101,619	88,231	84,142	78,988	78,988
Adj. R^2	0.580	0.581	0.596	0.596	0.602	0.603

This table presents the results of our tests examining the association between country-level LLRT and investment-*q* sensitivity from 2001–2015. The dependent variable (*I*) is the firm's total investment in year *t*, including physical and intangible investment, scaled by the lagged total replacement costs of the physical and intangible capital. We focus on the interaction term of *Q × LLRT*. *Q* is the firm's total *q* in year $t-1$, calculated as its market value divided by the total replacement costs of the physical and intangible capital. In column (1), we run a benchmark model without the interaction term. In columns (2)–(6), we respectively use five different country-level LLRT measures. All control variables are measured in year $t-1$. Appendix A summarizes all variable definitions. The *t* values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms are estimated but omitted for brevity. ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively.