Credit Ratings and Firm Innovation: Evidence from Sovereign Downgrades[*]

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June 2019

[*] The authors are grateful to Ling Cen, David Denis, Micah Officer, Jong-Min Oh (CICF discussant), Lynnette Purda (EFA discussant), Xuan Tian, Matthew Wynter (FMA discussant), Tong Zhou, Hong Zou, conference participants at the 2018 China International Conference in Finance, the 2018 Eastern Finance Association Annual Meeting, the 2018 Financial Management Association Annual Meeting, and the 2018 Hong Kong Junior Accounting Faculty Conference, as well as seminar participants at Tsinghua University for helpful comments and suggestions.

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Abstract

This study investigates how credit ratings affect firm innovation. By exploiting sovereign downgrades as an exogenous shock to corporate credit ratings, we show that a sovereign downgrade leads to significant reductions in innovation among firms that have a rating at the sovereign bound ex ante. The effect is concentrated in firms with high external finance dependence. Also, we identify the shift in debt choice towards bank loans and the increase in creditor control facilitated by greater use of covenants in loan agreements as potential channels of the causal relation. Further evidence suggests that firms are more likely to acquire innovative targets to mitigate the decline in innovativeness following downgrades. Since innovation is an important catalyst for economic growth, this study sheds light on the real effects of credit ratings on economic development.

JEL classification: G21; G24; G32; G34; H63; O30

Keywords: Credit ratings; Innovation; Sovereign rating downgrade; Creditor control; Mergers and acquisitions

1. Introduction

Financial markets play an important role in economic development. As a catalyst for economic growth, technological innovation has received considerable attention in the literature. Recent research shows empirical evidence on the impact of different groups of financial market players upon firm innovation activities. Aghion, Van Reenen, and Zingales (2013) find that the presence of institutional owners increases managerial incentives to innovate by reducing managers' career concerns with risky projects. Chemmanur, Loutskina, and Tian (2014) show that firms backed by corporate venture capital are more innovative because of venture capitalists' better knowledge of the industry and the technology as well as greater tolerance for failure. Brav, Jiang, Ma, and Tian (2017) document that hedge fund activists improve target firms' innovation efficiency through reallocation of innovative resources and redeployment of human capital. He and Tian (2013) find a negative causal effect of analyst coverage on firm innovation and argue that financial analysts exert too much pressure on managers to meet short-term goals and sacrifice investment in long-term innovative projects. He and Tian (2016) suggest that short sellers mitigate managerial myopia in investment decisions and improve corporate innovation. Despite the recent development of innovation literature, there is still very little evidence on how credit rating agencies, an important group of financial intermediaries, affect corporate innovation. This study aims to fill this void.

We argue that credit ratings play a significant role in firm innovation. From the perspective of capital providers such as debtholders, their lending decisions are likely to be affected by a firm's credit rating. Accordingly, credit ratings can influence a firm's financing cost, capital structure, and investment decisions, among others. Anecdotal evidence consistently suggests that managers are concerned about their firms' credit ratings, even in large and financially strong firms. For example, when the credit rating of Toyota Motor Corporation, one of the world's largest automotive manufacturers, was downgraded in March 2011 by Standard and Poor's (S&P), the firm responded in a statement that "the downgrade by S&P is regrettable and we do not take this rating change lightly" and indicated that its management decisions would be adjusted as a result.[1] Firm innovation is among the corporate policies that could be influenced in response to credit rating changes.

By exploiting the events of sovereign downgrades, this study investigates how credit ratings affect firm innovation. Specifically, rating agencies maintain a ceiling policy requiring that firms' ratings should not exceed the sovereign rating of their country of domicile. Therefore, in the event of sovereign downgrades, the variation in corporate ratings due to the ceiling policy is not an outcome of firm performance but may have real effects on corporate policies. In this study, we focus on investment in innovative projects, which is very different from ordinary investment such as capital expenditures examined in prior studies (e.g., Almeida, Cunha, Ferreira, and Restrepo, 2017), because (i) technological innovation is vital for a firm's long-term competitive advantage and a country's economic growth (Solow, 1957; Porter, 1992), (ii) unlike routine tasks, innovation is a long-term, risky, and idiosyncratic process (Holmstrom, 1989) and thus is prone to a variety of market frictions, given that intangible investments through R&D are especially difficult for the market to value, and (iii) as R&D spending has become a major component of aggregate corporate investment since the late 1990s (Dong, Hirshleifer, and Teoh, 2018), how financial markets shape the initiation and outcome of technological innovation by firms is an important question to investors, business practitioners, social scientists, policy makers, among others (He and Tian, 2018). This study adds to our understanding about the influence of financial market intermediaries

[1] See "Toyota stung by S&P downgrade," *MarketWatch*, March 4, 2011. Also, the Qantas Group, the largest airline company in Australia, considered the downgrade of its credit rating by S&P in December 2013 as "unprecedented pressures from external forces" (http://investor.qantas.com/DownloadFile.axd?file=/Report/ComNews/20131206).

on technological innovation by providing a novel piece of micro-level evidence.

Credit ratings could either positively or negatively affect corporate innovation. A firm's credit rating affects its access to capital market, the capacity to finance from debt investors, and the cost of capital. Credit rating downgrades can make it especially difficult for firms to finance innovation with external capital due to the inherent information asymmetry and illiquidity of innovative projects. Moreover, a credit rating downgrade may trigger covenant violations, which transfer control rights to creditors and give rise to creditor intervention (Manso, Strulovici, and Tchistyi, 2010; Nini, Smith, and Sufi, 2012). Prior studies suggest that creditors are concerned about the risk induced by innovative activities (e.g., Stiglitz, 1985; Gu, Mao, and Tian, 2017), as innovation is a long-term, unpredictable, and idiosyncratic investment in intangible assets with a high probability of failure (Holmstrom, 1989). Due to the asymmetric payoff structure of debt, creditors would suffer from the default risk arising from the failure of innovative projects but receive relatively fixed interest payments for innovation success and, as a result, may stifle borrowing firms' innovative activities (see Acharya and Subramanian, 2009; Hsu, Tian, and Xu, 2014). Therefore, strengthened creditor control following credit rating downgrades can lead to reductions in firms' innovative activities.

On the other hand, firms may make more investments in innovation in the event of a negative change in credit ratings. Credit rating agencies assess a firm's creditworthiness according to specific criteria that usually relate to financial ratios (e.g., the Debt/EBITDA ratio). Also, credit rating agencies set up salient thresholds arbitrarily at round numbers such as 1.5, 2.0, 3.0, etc. and map the ranges of each financial ratio to potential credit ratings (see Standard & Poor's Ratings Services, 2013). Thus, a firm's credit rating is affected by which bin it falls within across a set of financial ratios. To avoid possible deterioration in the rating criteria and consequent downgrades, higher-rated firms face greater pressures to meet short-term financial objectives and have less flexibility in expanding innovation expenditures (Graham, Harvey, and Rajgopal, 2005; Begley, 2015). The literature has shown substantial evidence that such short-term pressures can constrain managers' incentives to take on innovative projects (e.g., He and Tian, 2013; Gonzalez-Uribe and Xu, 2017; Chemmanur and Tian, 2018). If a negative change in credit ratings does take place, however, firms may obtain greater financial slack as the lowered rating implies a less strict restriction on financial performance and is easier to maintain.[2] Therefore, firms with a lower rating face fewer short-term pressures from credit rating criteria and are more likely to encourage innovation which can create long-term shareholder value.

In addition, although the literature has documented a significant decline in capital expenditures following credit rating downgrades (e.g., Almeida, Cunha, Ferreira, and Restrepo, 2017), the prediction about the effect of credit ratings on innovation is less clear-cut. In particular, it is possible that changes in credit ratings may have no impact on firm innovation. Unlike capital expenditures, investments in innovation are a relatively persistent series and thus less flexible (Lach and Schankerman, 1989; Li, 2011). Also, given that innovation is a long-term process, such decisions are often long-term-oriented. Consequently, R&D spending as well as innovation output might not respond to shocks (e.g., credit rating changes) in the same manner as capital investment does (Griffith, Redding, and Van Reenen, 2004).

Collectively, the above arguments suggest that how credit ratings affect firm innovation is an

[2] To illustrate, consider two otherwise identical firms 1 and 2, both of which have the same Debt/EBITDA ratio equal to 2.9. Assume that credit rating agencies rate firms with Debt/EBITDA in [2.0-3.0) at A, while firms with Debt/EBITDA in [3.0-4.0) are BBB-rated. Thus, the two firms receive the same rating of A ex ante. Suppose now that there is an exogenous constraint on firm 1 that prevents its corporate rating from being above BBB, although its Debt/EBITDA remains unchanged. After the downgrade from A to BBB, firm 1 is much more flexible to adopt EBITDA-decreasing policies (but also able to maintain its best possible rating BBB) until its Debt/EBITDA ratio reaches 4.0, compared to firm 2.

interesting and important empirical question. To investigate this question, researchers need to overcome empirical challenges. For example, the literature documents that firm management has incentives and means to influence credit ratings (e.g., Alissa, Bonsall IV, Koharki, and Penn, 2013; Jung, Soderstrom, and Yang, 2013). Also, credit rating is endogenous and may reflect the potentials of R&D projects. This means the relation between credit ratings and firm innovation may be subject to reverse causality. Moreover, the possibility of omitted variable bias hinders convincing inferences from traditional cross-country regressions, because credit ratings often vary with improvement or deterioration in firm financial health and macroeconomic conditions. To address the endogeneity concerns and establish causality, we take advantage of rating agencies' sovereign ceiling policies that require firms' ratings not to surpass the sovereign rating of their country of domicile and investigate the asymmetric impact of sovereign downgrades on firms with a credit rating at the sovereign bound ex ante (bound firms) relative to firms that are below the bound (non-bound firms).

Our identification strategy relies on a difference-in-differences (DiD) specification. Treated firms are the bound firms affected by sovereign downgrades (i.e., their country's sovereign rating is downgraded and they have a rating at the sovereign bound before the downgrade). Nontreated firms include non-bound firms and the bound firms that do not experience sovereign downgrades. Our baseline analysis shows that bound firms reduce innovation following a sovereign rating downgrade, relative to non-bound firms. Specifically, treated firms reduce R&D expenditures, file fewer patent applications, and generate patents with fewer citations (i.e., lower quality). The results suggest that firms become less innovative in terms of both quantity and quality when they experience an exogenous deterioration in credit ratings. This identification strategy enables us to establish a causal effect of credit ratings on firm innovation activities.

To explore the potential mechanism through which a rating downgrade affects corporate innovation, we first show that the reduction in innovative activities following sovereign downgrades is more pronounced in firms that are more dependent on external financing to fund investment. Further, we find that the debt structure of treated firms shifts from public bonds towards bank loans in the event of sovereign downgrades, while the overall financial leverage exhibits an insignificant change around downgrades. Consistent with the notion that lower credit quality reduces a firm's use of public debts relative to bank loans and bank lenders are more effective monitors than public bondholders (e.g., Diamond, 1991; Denis and Mihov, 2003), the results imply creditor control and intervention as a mechanism underlying the causal relation between credit ratings and firm innovation decisions. In support of the interpretation, we also find a significant increase in the use of covenants in the loans borrowed by bound firms around sovereign downgrades. The higher intensity of covenants in loan agreements following rating downgrades enhances creditor control, which impedes firm innovation.

We perform a battery of additional tests to check the robustness of our findings. To address the concern that our results might be driven by the differences in firm characteristics, we conduct nearest-neighbor matching and implement entropy balancing, respectively, which allow us to ensure covariate balance along various characteristics between treated and nontreated firms. Both analyses confirm our main findings. Also, our placebo test shows that firms display a similar pattern of innovative activities prior to sovereign downgrades and validates the parallel trends assumption in difference-in-differences estimation.

We conduct another placebo test to deal with the concern that economic recessions lead to sovereign downgrades and reductions in firm innovation. Because economic performance is strongly correlated among neighboring countries (Ades and Chua, 1997; Conley and Ligon, 2002), sovereign downgrades in a neighboring country should exhibit significant effects on the focal country's corporate innovation if economic factors other than credit ratings drive our main results. We do not find significant changes in firm innovation in placebo countries that are not downgraded but have a neighbor experiencing a sovereign downgrade. Hence, our findings cannot be interpreted as a consequence of financial market turmoil or adverse economic conditions at the time of sovereign debt impairments. Moreover, it is unlikely that the bound firms (which have higher ratings and better creditworthiness) are adversely affected by macroeconomic shocks to a greater extent than those non-bound firms.

In addition, we find little evidence that bound firms change their innovation activities following sovereign *upgrades*, consistently indicating that our findings are not driven by economic shocks which might be correlated with rating changes. In contrast to the significant impact of sovereign downgrades on bound firms, the insignificant effect of upgrades is consistent with the asymmetric nature of the sovereign ceiling policy adopted by rating agencies.

To further mitigate the concern that the observed effect of sovereign downgrades might be explained as a result of greater exposure to the government's health among bound firms than non-bound firms, we perform a placebo test in which firms with a rating one or two notches below the sovereign are considered as bound firms. In particular, if the government exposure explanation is valid, these firms should also receive government support (e.g., higher government ownership, greater exposure to government spending, etc.) relative to firms with a rating much lower than the sovereign. This placebo test suggests that our findings are unlikely to be due to differential exposure to government shocks between bound and non-bound firms.

Last, we extend our analysis and examine the impact of sovereign downgrades on firm acquisition decisions. Our results show that the changes in acquisition spending or frequency around credit rating downgrades are not significant, suggesting that the adverse impact induced by financing friction and creditor control is offset by the attractiveness of acquiring undervalued targets at the time of sovereign debt impairments (Shleifer and Vishny, 2003; Erel, Liao, and Weisbach, 2012). However, we find that bound firms are significantly more likely to acquire innovative targets following downgrades and that an acquisition of innovative targets mitigates the decline in their R&D expenditure and patent quality. Consistent with the literature, the evidence indicates that firms strategically undertake acquisitions to maintain or improve innovativeness (e.g., Sevilir and Tian, 2012; Phillips and Zhdanov, 2013; Bena and Li, 2014).

This study contributes to the literature in the following aspects. First, to our knowledge, this study is the first to establish the causal effect of credit ratings on firm innovation. By focusing on innovation, which is an important catalyst for economic growth, our evidence highlights the link between sovereign debt impairments and the real economy. Second, this study provides new insights into the effects of credit ratings, by identifying creditor control and intervention as a potential mechanism underlying the causal relation between rating downgrades and firm innovation decisions. Specifically, we find a significant increase in the use of bank loans versus public debts and in the intensity of financial covenants imposed in loan contracts following downgrades. The evidence suggests why rating downgrades matter, thereby complementing prior studies that focus exclusively on the response of affected firms (e.g., Almeida, Cunha, Ferreira, and Restrepo, 2017). Third, from an international perspective, this paper adds to the innovation literature by showing how market players affect corporate patenting activities. Our findings are particularly germane because credit rating information is extensively used by capital market participants. Also, by exploring the acquisition activities around rating downgrades, this study contributes to the growing literature that documents the important role of mergers and acquisitions in firm innovation (e.g., Sevilir and Tian, 2012; Phillips and Zhdanov, 2013; Bena and Li, 2014).

The rest of this paper proceeds as follows. Section 2 describes the sample construction and the variables. Section 3 presents the primary empirical results. Robustness checks and additional tests are provided in Sections 4-5. Section 6 investigates the impact of sovereign downgrades on corporate acquisitions. Section 7 concludes the paper.

2. Sample construction and research design

2.1. Data and sample construction

We begin our sample construction by retrieving the patent data from the REGPAT database provided by the Organization for Economic Co-operation and Development (OECD). The database includes patent applications filed to the European Patent Office (EPO) and the Patent Co-operation Treaty (PCT) from 43 countries during 1977-2013. Compared to the National Bureau of Economic Research (NBER) patent database of utility patents granted by the U.S. Patent and Trademark Office (USPTO), the OECD REGPAT database provides a more comprehensive coverage of patenting activities in non-U.S. firms (see Maraut, Dernis, Webb, Spiezia, and Guellec, 2008).[3] We require a firm to be covered by the REGPAT database to be included in our sample.[4]

Next, following the literature (Adelino and Ferreira, 2016; Almeida, Cunha, Ferreira, and Restrepo, 2017), we use the rating information provided by Standard and Poor's. The literature suggests that S&P is more active in revising ratings and tends to lead other credit rating agencies

[3] We also compare the coverage of patent data between the OECD and NBER patent database. Overall, the OECD patent database has a more comprehensive coverage of patent applications than the NBER patent database. The advantage is especially obvious when focusing on non-U.S. patent applications.

[4] While this requirement mitigates the possible measurement error related to patents, it results in a smaller number of treated firms in our sample relative to Almeida, Cunha, Ferreira, and Restrepo (2017).

in rating revisions (Kaminsky and Schmukler, 2002; Brooks, Faff, Hillier, and Hillier, 2004). Further, credit rating agencies typically assign different types of ratings based on the maturity (short-term/long-term) and the currency denomination of obligations (foreign/local currency). We focus on foreign currency long-term issuer ratings because this type is most likely to be bound by sovereign credit ratings (Almeida, Cunha, Ferreira, and Restrepo, 2017). Given the merits of S&P credit ratings, we obtain the information on corporate and sovereign credit ratings from the Capital IQ Ratings database. We manually match the patent applicants in the REGPAT database to the public firms in the Capital IQ Ratings database, by company name and country of domicile. Non-bound firms without a credit rating are excluded, as bound firms are necessarily rated.

Last, we collect firm-level financial data from the Compustat Global database for non-U.S. firms and use the Compustat North America database for U.S. firms. By excluding financial firms (SIC codes 6000-6999), our sample consists of nonfinancial firms in the intersection of Capital IQ Ratings, REGPAT, and Compustat databases during 1995-2012.[5] Appendix A presents the list of treated firms as well as their country of domicile, downgrade year, and sovereign ratings at the beginning and end of the downgrade year. Our sample includes 41 treated firm-years from 12 different countries.

2.2. Variables

Following prior studies (e.g., Fang, Tian, and Tice, 2014), we use a firm's R&D expenditure and patenting activity to measure innovation. R&D expenditure measures a firm's innovation input, computed as R&D expenses scaled by total assets, multiplied by 100 (*RDTA*). Based on the

[5] Given that the REGPAT patent data are available up to 2013, our sample period ends in 2012 to allow for the availability of one-year-ahead innovation measures.

information retrieved from the OECD REGPAT database, we construct two measures to capture a firm's innovation quantity (*LN_PAT*) and quality (*LN_CITE*), respectively. The first is the number of patent applications filed in a year, as the application year captures the actual time of innovation (Griliches, Pakes, and Hall, 1988). The second is the average number of non-self-citations received subsequently on the patents filed in a year. Since a patent can receive citations over a long period beyond the last year of our data on citations, we adjust this measure of innovation quality to address the truncation problem following Hsu, Li, and Lin (2016). For each patent, we compute its adjusted citations as the number of subsequent citations received on this patent divided by the average number of subsequent citations received on all patents categorized in the same technology category[6] and filed in the same year as the focal patent. Finally, due to the right-skewed distributions of patent counts and citations, we use the natural logarithm of one plus the actual values in our analysis. The proxies for firm innovation are measured one year ahead. Considering the long-term nature of investment in innovation, we also test the robustness using the innovation measures over the three years ahead.

To capture the effect of a sovereign downgrade on bound firms, we construct an indicator variable that takes the value of one if a firm has a rating at the sovereign bound in year t-1 ($BOUND_{t-1}$), an indicator variable that takes the value of one if a firm's country rating is downgraded in year t ($DOWN_t$), and the interaction term $BOUND_{t-1} \times DOWN_t$ ($BOUND\_DOWN_t$).[7] We also include control variables that are commonly used in the innovation

[6] A patent's technology category is defined according to the first digit of International Patent Classification (IPC) issued by the EPO. IPC is a hierarchical patent classification system that separates the whole body of technical knowledge using the hierarchical levels (i.e., section, class, subclass, group, and subgroup) in descending order of hierarchy. Each classification term consists of a symbol. The first digit is a capital letter as the *section* symbol, followed by a two-digit number to give an indication of the *class*. The fourth digit is a capital letter to indicate the *subclass*. In the main tests, we rely on the first digit of IPC, where patents are classified according to eight sections (the highest level of hierarchy of the classification). Our results are very similar if we instead use narrower classifications such as the 3-digit and 4-digit IPC.

[7] Our sample includes rare cases in which a firm's credit rating surpasses the sovereign ceiling ex ante. Such firms

literature to account for the time-varying differences across firms. For firm characteristics, we control for firm size (*LN_AT*), Tobin's Q (*Q*), leverage (*LEV*), R&D expenditure (*RDTA*)[8], profitability (*ROA*), fixed assets (*PPETA*), capital expenditure (*CAPEXTA*), financial constraint (*SAINDEX*), and firm age (*LN_AGE*). For country characteristics, we include GDP per capita (*LN_GDPPC*), GDP growth (*GPDGROWTH*), and inflation rate (*INFLATION*). Variable definitions are provided in Appendix B. To minimize the influence of outliers, we winsorize all continuous variables at the top and bottom 1%. The summary statistics of the variables in our primary tests are presented in Table 1.

[Insert Table 1 about here]

As shown in Panel A of Table 1, on average, the R&D expense of a firm-year in our full sample is 2.6% of total assets, with 44.3 patent applications per year, and each patent application receives 0.9 non-self-citations. The average patent (citation) count of our sample is higher (lower) compared to prior studies using the NBER patent database that only records patent grants (i.e., patent applications that are eventually granted) (e.g., Acharya and Subramanian, 2009; He and Tian, 2013; Fang, Tian, and Tice, 2014); our study uses the REGPAT database that covers patent applications. The summary statistics of our control variables are comparable to prior studies (e.g., Fang, Tian, and Tice, 2014). The average firm has total assets of $15.3 billion, return on assets of 13.0%, property, plant, and equipment scaled by total assets of 33.6%, financial leverage of 28.8%, Tobin's Q of 1.7, and is 25.5 years old since first Compustat record.[9]

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have great exposure to foreign countries (e.g., with foreign assets, high export earnings, foreign parents, etc.) and demonstrate strong resilience to the default risk of the sovereign (Almeida, Cunha, Ferreira, and Restrepo, 2017). We obtain similar results if these firms are excluded.

[8] We follow the literature and control for lagged *RDTA*. Nevertheless, our results throughout the paper are robust to excluding it as a control variable.

[9] Given that U.S. firms make up a large proportion of our sample, we also conduct robustness checks by excluding U.S. firms throughout our analyses. The results are quite robust and available upon request.

To test the validity of our identification strategy, in Panel B of Table 1, we compare the changes in corporate ratings between bound and non-bound firms around sovereign downgrades. *NUMRATING* is the numerical scale S&P credit rating (from 1 for the lowest rating SD/D to 22 for the highest rating AAA). On average, bound firms lose 1.49 notches following a sovereign downgrade due to the ceiling policy. In comparison, non-bound firms experience virtually no change in their ratings. The difference-in-differences is -1.43 notches, significant at the 1% level. The result confirms the differential impact of sovereign downgrades on bound and non-bound firms and therefore validates our empirical design.

3. Baseline analysis

To examine whether sovereign downgrades adversely affect the innovation of bound firms, we estimate the following regression model:

$$INNOVATION_{i,t+1} = \alpha + \beta_1 BOUND\_DOWN_{i,t} + \beta_2 BOUND_{i,t-1} + \beta_3 DOWN_{i,t} + \gamma X_{i,t-1} + \delta_t + \delta_i + \varepsilon_{i,t}, \quad (1)$$

where *i* indexes firm, *t* indexes year, $INNOVATION_{i,t+1}$ is one of the innovation measures in year *t*+1 (i.e., $RDTA_{t+1}$, LN_PAT_{t+1}, and LN_CITE_{t+1}), $X_{i,t-1}$ is a vector of firm and country characteristics, δ_t is year fixed effects, δ_i is firm fixed effects. Standard errors are clustered at the country level to correct for within-country residual correlation (Adelino and Ferreira, 2016). The coefficient on the interaction term (*BOUND_DOWN*) is a DiD estimator, representing the difference in innovation intensity between treated firms and nontreated firms following a sovereign downgrade relative to the difference before the downgrade.

Table 2 reports the estimates of Equation (1). The coefficients of *BOUND_DOWN* are negative and statistically significant across all the columns, suggesting that bound firms reduce their innovation more than other firms. Specifically, we find that bound firms reduce R&D expenditures by 7.3% of the sample mean, patent counts by 18.9%, and patent citations by 16.3%, relative to other firms in the year after a sovereign downgrade.

[Insert Table 2 about here]

The results show that not only R&D expenditures but also patenting activities are affected one year after a rating downgrade. Although it may be less flexible to entirely terminate innovative projects than to cut down R&D spending, a firm's patenting activities can be interrputed or delayed, leading to an immediate decrease in the quantity and quality of patent applications following downgrades. The evidence is consistent with the notion that patenting is a long process and involves multiple stages before a patent application is filed (see Ozluturk, Kimmelblatt, and Patel, 2013).

In addition, we examine the changes in innovation among treated firms versus nontreated firms over the three-year period following a sovereign downgrade. Consistent with our main findings, untabulated results indicate that sovereign downgrades have a significant impact on bound firms in their innovation activities beyond one year.

In the baseline regressions, we follow prior studies (e.g., Fang, Tian, and Tice, 2014) and set missing R&D to zero to mitigate the loss of observations. We perform robustness tests (untabulated) and find that our findings are very similar if missing R&D values are not replaced with zero.

Last, our results might be alternatively interpreted as a consequence of financial market turmoil or adverse economic conditions at the time of sovereign debt impairments. However, it is unlikely that the bound firms (which have higher ratings and better creditworthiness) are affected by such shocks to a greater extent than those non-bound firms. Although we control for time-varying country-level macroeconomic variables in the regressions, another potential explanation for our results is that an omitted variable coinciding with sovereign rating downgrades could be the underlying cause of changes in innovation. Nevertheless, as our identification strategy uses shocks that affect different countries at different times, it is unlikely that an omitted variable would vary every time with the rating downgrades. Moreover, in untabulated tests, we further control for country-by-year fixed effects to capture the time-varying control-level economic factors. The results are unchanged after including the high-dimensional fixed effects.

4. Robustness tests

4.1. Matched sample analysis

Our baseline regressions show that sovereign downgrades adversely affect innovation activities of bound firms to a greater extent. The results, however, could be confounded by the differences in firm characteristics between bound and non-bound firms. To address this concern and facilitate a sharper identification of the effect, we perform a matched sample analysis. Specifically, we construct a balanced matched sample using Mahalanobis Distance Matching (MDM), which was first proposed by Rubin (1980) and implemented by Abadie, Drukker, Herr, and Imbens (2004). To this end, we conduct nearest-neighbor matching that allows us to minimize the Mahalanobis distance along various characteristics between treated and control firms, following Almeida, Campello, Laranjeira, and Weisbenner (2011) and Almeida, Cunha, Ferreira, Restrepo (2017).

The one-to-one MDM uses nine covariates, including seven firm characteristics (size, leverage, Tobin's Q, cash flow, research and development expenses, tangibility, and external finance dependence) and two country-level macroeconomic factors (GDP growth and inflation). We also require exact matching on industry (based on Fama-French 12 industry classification) and year. This matching procedure generates 39 pairs of treated and matched control firms. As shown in Panel A of Table 3, the t-test and Kolmogorov-Smirnov test suggest that the treated and control firms are balanced in terms of similar means and distributions along all the covariates.

[Insert Table 3 about here]

Panel B of Table 3 reports the results of the difference-in-differences analysis using the matched sample. First, we focus on the change in innovation measures around sovereign downgrades. We show that *treated* firms experience a significant decline in innovation activities after downgrades, with *p*-value < 0.01 and < 0.1 when innovation is proxied by *RDTA* and *LN_PAT*, respectively. In contrast, *control* firms slightly increase their innovation activities. Second, we compare the difference in innovation measures between treated and control firms. In the year *before* a downgrade, there is no significant difference in any of the innovation measures between treated and control firms, suggesting that our matched sample is not only balanced in firm characteristics but also in innovation measures. In the year *after* a downgrade, there are statistically significant differences between treated and control firms in *RDTA* and *LN_CITE* (*p*-value < 0.01). Finally, the difference-in-differences estimators are all significantly negative when we measure firm innovation by *RDTA* (*p*-value < 0.01), *LN_PAT* (*p*-value < 0.05), and *LN_CITE* (*p*-value < 0.1).

In the preceding analysis, we do not perform exact matching on country to obtain a better balanced matched sample. It is possible that our results are driven by the differences in country-level unobservable factors when treated and control firms are not from the same country. To rule out this possibility, we perform the same analysis using country-adjusted innovation measures. We present the results in Panel C of Table 3. The results from this analysis are largely consistent with those in Panel B and further confirm our baseline finding.[10]

4.2. Entropy balancing

In our sample, only a small fraction is categorized as treated firms. Such an unbalanced sample could create noise in our estimation because the average treated firm might not be comparable to the average nontreated firm. To mitigate this concern, we employ the entropy balancing approach to reduce the differences in fundamentals between treated and nontreated firms that may drive the results (see Hainmueller 2012; McMullin and Schonberger 2018; Shroff, Verdi, and Yost, 2017). Specifically, the entropy balancing technique preserves the full sample and re-weights observations to achieve covariate balance (in terms of mean and variance) between treated and nontreated firms. Thus, entropy balancing ensures that our treated and nontreated samples are similar ex ante along a variety of characteristics.

In Table 4, we perform entropy balancing on the full sample and report the baseline regression results after re-weighting observations. In Panel A, we compare the mean and variance before and after entropy balancing between treated and nontreated firms along nine covariates, including seven firm characteristics (size, leverage, Tobin's Q, cash flow, research and development expenses, tangibility, and external finance dependence) and two macroeconomic factors (GDP growth and inflation). After entropy balancing, the mean and variance are virtually identical between treated and nontreated firms along these covariates, suggesting that the average treated

[10] In addition, we repeat the difference-in-differences analysis using various combinations of matching covariates to construct the matched sample. We still find a significant decrease in innovation among treated firms relative to control firms. All of our matching methods yield consistent results, indicating that our findings are not sensitive to matching criteria. The results are not tabulated for brevity but available upon request.

firm is comparable to the average nontreated firm.

[Insert Table 4 about here]

In Panel B of Table 4, we rerun the baseline regressions with the re-weighted sample. The coefficients on *BOUND_DOWN* are negative and significant at the 5% level or better, consistent with our main finding. The results based on entropy balancing allow us to more comfortably interpret the reduction in innovation in the treated firms as caused by rating downgrades as opposed to potential differences between treated and nontreated firms.

4.3. Placebo tests

A potential concern regarding our baseline results is that sovereign downgrades are caused by economic recessions, which in turn lead to reductions in firm innovation. To address this concern, we conduct a placebo test by exploiting the downgrades of sovereign ratings in neighboring countries. Prior studies (e.g., Ades and Chua, 1997; Conley and Ligon, 2002) show that economic performance is strongly correlated among neighboring countries. Thus, if economic factors other than credit ratings drive our findings, sovereign downgrades in a neighboring country should affect the focal country's corporate innovation. To examine whether this concern is valid, we falsely set the dummy for sovereign downgrades equal to one if a firm's country is not downgraded in year *t* but at least one neighboring country is downgraded ($NBDOWN_t$) and include in Equation (1) this placebo indicator as well as the corresponding interaction term $BOUND\_NBDOWN_t$, in place of the actual indicator $DOWN_t$ and the interaction term $BOUND\_DOWN_t$.

The results are reported in Panel A of Table 5. We find that the coefficient of *BOUND_NBDOWN*, which is based on the placebo indicator, is insignificant, implying no significant change in any proxies for innovation in placebo countries that are not downgraded but have a neighbor experiencing a sovereign downgrade. The placebo test suggests that our main results are not driven by adverse economic conditions, lending further support to the causal effect of credit ratings on firm innovation.

[Insert Table 5 about here]

Another concern stems from the possibility that bound firms may be more exposed to the government's health and have differential exposure to government shocks than non-bound firms. If sovereign downgrads simply reflect a deterioration in government fiscal position, firms that receive more support from the government ex ante (e.g., higher government ownership, greater sensitivity to government spending, etc.) are more likely to be affected at the time of sovereign debt impairments. To refute the alternative explanation that the observed effect on bound firms may be driven by their greater government exposure, we perform a placebo test in which firms with a rating one or two notches below the sovereign are defined as bound firms. Relative to firms with a rating more than two notches below the sovereign, the placebo bound firms should be more exposed to the government's health and hence reduce innovation to a larger extent if the government exposure explanation is valid.

The regression results of this placebo test are provided in Panel B of Table 5. We find no difference in innovation activities between the two groups of firms following soverign downgrades. Consistent with Almeida, Cunha, Ferreira, and Restrepo (2017), the insignificant effect on the placebo bound firms indicates that our findings do not simply capture higher-rated firms which might have greater government exposure, but rather firms that are bound by the sovereign ceiling.

In addition, to further validate the key assumption of pre-treatment parallel trends in difference-in-differences estimation, we perform an alternative placebo test where we focus on each country's first sovereign downgrade in our sample period and change the timing of these downgrades (see Roberts and Whited, 2013).[11] Specifically, we falsely assume that a country's first downgrade occurs three years before it actually does. For example, in this placebo test, the sovereign rating of Mexico was downgraded in 2006 rather than the actual downgrade year of 2009. Thus, we use a placebo indicator variable that is equal to one if a firm's country is downgraded for the first time in year t+3 ($TDOWN_t$) and the corresponding interaction term $BOUND\_TDOWN_t$ in the regressions. The results are presented in Panel C of Table 5.

As shown in Panel C of Table 5, the placebo treatment effect is statistically indistinguishable from zero. The results suggest that firms have similar characteristics prior to actual sovereign downgrades and support the validity of our identification strategy.

4.4. The effect of sovereign rating upgrades

Our analysis shows that a sovereign downgrade negatively affects the innovation activities of bound firms in the country. A natural question arising from the baseline results is how sovereign upgrades affect firm innovation. In this subsection, we report additional results in response to this question. Specifically, we define an indicator variable that takes a value of one if a firm's country rating is upgraded in year t (UP_t). Then we estimate a regression model similar to Equation (1) by replacing the indicator variable *DOWN* with *UP* and the interaction term *BOUND_DOWN* with *BOUND_UP*. Similarly, the coefficient on the interaction term *BOUND_UP* reflects the effect of a sovereign upgrade on corporate innovation intensity.

We present the regression results in Table 6. The coefficients of *BOUND_UP* are statistically insignificant, indicating that the changes in innovation of bound firms are not distinguishable from

[11] We focus on the first downgrade for each country to ensure that the post-treatment period of a downgrade is not commingled with the pre-treatment period of another downgrade in the same country.

zero following sovereign upgrades. Again, the results indicate that the changes in firm innovation are not caused by economic shocks, which might be correlated with rating changes. Also, relative to the significant effect of downgrades upon bound firms, the insignificant effect of upgrades is consistent with the asymmetric nature of the sovereign ceiling policy adopted by rating agencies. Taken together, the evidence further corroborates our interpretation.

[Insert Table 6 about here]

5. Potential mechanism

5.1. Dependence on external finance

In this section, we perform further tests to explore the underlying mechanism through which credit rating affects innovation. To begin with, we investigate the heterogeneity in the effect of sovereign downgrades across firms with different levels of external finance dependence. Credit ratings are useful for investors, especially for debt providers, to evaluate the default risk of borrowers and figure out appropriate financing terms in accordance with the investment risk. As a result, a downgrade of credit rating is more likely to affect the firms that rely more on external finance, ceteris paribus. To test this conjecture, we follow prior studies (e.g., Rajan and Zingales, 1998; Duchin, Ozbas, and Sensoy, 2010; Hsu, Tian, and Xu, 2014) and construct a proxy for external finance dependence. Specifically, we collect the annual data of all public U.S. firms from Compustat and compute each firm's dependence on external finance as capital expenditures minus funds from operations, divided by capital expenditures. Then we define each three-digit SIC industry's external finance dependence based on the median among all the U.S. firms in that industry in a year. Following Rajan and Zingales (1998), we assume that industry characteristics in the U.S. carry over to other countries, in order to measure an industry's external finance dependence for each country in our sample. Therefore, the industries in which a higher proportion of investment is not financed by cash flow from operations (i.e., is funded by external financing) are considered as more dependent on external finance.

Next, we divide our main sample based on the annual median external finance dependence and estimate Equation (1) for the two subsamples of less and more external-finance-dependent firm-years, respectively. The results are reported in Table 7. We find that the effect of sovereign downgrades on bound firms' innovation is mainly concentrated in the firms with higher dependence on external finance, while less external-finance-dependent firms are not significantly affected.

[Insert Table 7 about here]

5.2. Changes in debt structure

We show in the previous subsection that external finance dependence aggravates the adverse impact of sovereign downgrades on the innovation of bound firms. In this subsection, we further investigate whether firms change their sources of financing following downgrades. Bank loans and public bonds are major sources of corporate debt financing. Prior studies (e.g., Diamond, 1991; Denis and Mihov, 2003) find that lower credit quality is associated with less use of public debts versus bank loans, because bondholders, unlike informed financial intermediaries such as banks, are less likely to gather private information and effectively monitor a firm to deal with information asymmetry. Therefore, a firm's credit rating, as an indicator of credit quality, can affect its choice of debt source.

Our results in Table 8 show the effect of sovereign downgrades on firms' financing decisions. In Columns 1 and 2, we examine the changes in capital structure following a downgrade. Capital structure is proxied by total debt ratio and long-term debt ratio, respectively. In both regressions, the coefficients of *BOUND_DOWN* are insignificant, suggesting that sovereign downgrades do not lead to significant changes in financial leverage (either total or long-term) in bound firms relative to non-bound firms.

[Insert Table 8 about here]

We further analyze whether sovereign downgrades affect a firm's choice between bank debt and public debt. Following Lin, Ma, Malatesta, and Xuan (2013), we obtain the debt structure information from Capital IQ and use the ratio of bank debt to total debt to proxy for a firm's debt structure. The results are presented in Column 3 of Table 8. The significantly positive coefficient on *BOUND_DOWN* indicates that bound firms increase the use of bank loans as their source of debt financing in the event of sovereign downgrades, despite insignificant changes in the overall debt ratio as shown earlier. Taken together, these results imply that bank lenders gain a greater representation in bound firms following downgrades, giving rise to greater creditor control and intervention. In connection with our main findings, the evidence is consistent with the notion that banks discourage firm innovation due to the payoff structure of debts and the highly risky nature of innovative projects (Stiglitz, 1985; Acharya and Subramanian, 2009). Thus, the tests in this subsection uncover a specific mechanism – increased use of bank loans and consequently intensified creditor control – through which rating downgrades impede firm innovation.

5.3. Changes in covenant intensity

Last, we provide evidence on the changes in the use of covenants in loan contracts around a sovereign downgrade. The use of covenants is an important mechanism to mitigate the reduction in debtholder wealth induced by agency problems and to facilitate creditor intervention in the event of technical defaults (see Chava and Roberts, 2008; Nini, Smith, and Sufi, 2012). To the extent that creditor control leads to the reductions in corporate innovation following sovereign downgrades, we should also observe an increase in the use of covenants, which enable banks to exert greater influence over borrowing firms.

To estimate the impact of sovereign downgrades on the covenant intensity of loans borrowed by bound firms, we follow Bradley and Roberts (2004) and track the total number of covenants imposed in each loan agreement from DealScan. We use the number of covenants to measure covenant restrictiveness because this measure is least subject to data unavailability. Moreover, even without explicit restrictions on firm innovation, financial covenants (e.g., the maximum Debt/EBITDA covenant) can potentially affect borrowers' innovation decisions, since borrowers have incentives to improve the covenant variable and avoid costly technical defaults by reducing R&D spending, which is expensed as incurred and subtracted from revenues (Demiroglu and James, 2010).

The regression results are reported in Table 9. The tests are conducted at the loan level in Column 1 and firm level in Column 2 (where the dependent variable is the average number of covenants in new loans borrowed by a firm in a year). Consistent with our conjecture, creditors impose more covenants in the loans lent to a bound firm when the firm country's sovereign rating is downgraded.[12] In sum, the results indicate that rating downgrades induce greater use of covenants in the bank loans borrowed by treated firms. The greater use of bank debt and the higher intensity of covenants in loan agreements enhance creditor control, which impedes firm innovation.

[Insert Table 9 about here]

[12] In untabulated tests, we also find a significant increase in loan spreads among bound firms following sovereign downgrades, suggesting that the observed greater use of covenants is not a trade-off against charging a lower loan spread by creditors.

6. Credit rating downgrades and corporate acquisitions

Our evidence so far shows that credit rating downgrades have a negative effect on firm investment in innovative activities. In this section, we extend our analysis by examining the changes in mergers and acquisitions (M&As) following sovereign downgrades. Prior research finds that bound firms reduce capital expenditures (i.e., investment in fixed assets) at the time of a sovereign downgrade (Almeida, Cunha, Ferreira, and Restrepo, 2017), whereas we still know little about the effect of rating downgrades on a firm's investment in the ownership of another entity through M&As. An investigation into this question can help us better understand the impact of credit ratings on various investment decisions. Moreover, as a firm can promote innovation through acquisitions of other innovative firms, M&As play an important role in enhancing acquiring firms' innovativeness (Sevilir and Tian, 2012). Therefore, we first test the changes in M&A decisions following downgrades and next show how acquisitions affect bound firms' innovation at the time of a sovereign downgrade.

First, we examine whether bound firms change acquisition spending after sovereign downgrades. The reason is twofold. Our main findings suggest that rating downgrades give rise to creditor control and intervention, which could restrain a firm from making acquisitions and lead to a reduction in M&A transactions. On the other hand, since sovereign downgrades tend to coincide financial market turmoil or adverse economic conditions, depressed asset prices during such periods may represent attractive investment opportunities for bound firms, which are more creditworthy and less likely to be undervalued than other firms including potential targets. Hence, bound firms may take advantage of the relative misvaluation to purchase relatively cheap assets and increase acquisition expenditures as a consequence (Shleifer and Vishny, 2003; Erel, Liao, and

Weisbach, 2012).

To test this conjecture, we use the M&A transaction value reported in SDC Platinum and perform our analysis at the firm level. Specifically, we aggregate the transaction value for each deal to compute the total dollar amount spent on M&As for each firm-year, scaled by lagged total assets (*ACQVALUE*). The acquisition measure is set to zero for firms not making any acquisitions in a year. In addition, we use the total number of M&A transactions a firm undertakes in a year as another acquisition measure (*ACQNUM*). We replace the dependent variable in Equation (1) with the acquisition measures individually and report the regression results in Table 10.

[Insert Table 10 about here]

As is shown in Columns 1 and 2 of Table 10, the coefficients on the interaction term are insignificant at any conventional levels, indicating that bound firms do not significantly change their acquisition spending or frequency after sovereign downgrades. The results suggest that the attractiveness of acquiring undervalued targets at the time of sovereign downgrades offsets the adverse impact caused by creditor interventions.

Next, we focus on M&A deal characteristics and provide evidence on the change in target innovativeness around rating downgrades. Target innovativeness (*INNOVT*) is an indicator variable that equals one for innovative targets – the target firm acquired in a deal has filed at least one patent application in the past five years. To construct this measure, we match the patent applicants in the REGPAT database to the target firms in SDC Platinum, by company name and country. We again use the difference-in-differences specification and further control for deal characteristics.

We present the regression results in Column 3 of Table 10. The coefficient estimate of *BOUND_DOWN* is positive and significant, suggesting that bound firms become more selective and are more likely to acquire innovative targets after sovereign downgrades. Despite a significant reduction in innovation input and output following downgrades, as shown in our baseline analysis, firms appear to maintain or enhance their innovativeness by taking advantage of depressed asset prices and acquiring innovative firms. Thus, our results are consistent with the emerging research showing that firms strategically make acquisitions to improve innovation (Sevilir and Tian, 2012; Phillips and Zhdanov, 2013; Bena and Li, 2014).

Finally, we explore how acquisitions of innovative targets affect the impact of rating downgrades on firm innovation. To this end, we estimate the following model:

$$INNOVATION_{i,t+1\sim t+3} = \alpha + \beta_1 BOUND\_DOWN_{i,t} + \beta_2 BOUND_{i,t-1} + \beta_3 DOWN_{i,t} + \beta_4 BOUND\_DOWN_{i,t} \times NUMINNOVT_{i,t+1} + \beta_5 BOUND_{i,t-1} \times NUMINNOVT_{i,t+1} + \beta_6 DOWN_{i,t} \times NUMINNOVT_{i,t+1} + \beta_7 NUMINNOVT_{i,t+1} + \gamma X_{i,t-1} + \delta_t + \delta_i + \varepsilon_{i,t}, \quad (2)$$

where i indexes firm, t indexes year, $INNOVATION_{i,t+1\sim t+3}$ is one of the innovation measures over three years from year t+1 to year t+3, $NUMINNOVT_{i,t+1}$ is the number of innovative firms acquired in year t+1, $X_{i,t-1}$ is a vector of firm and country characteristics, δ_t is year fixed effects, δ_i is firm fixed effects. We focus on the coefficient estimate of β_4, which captures the outcome of acquiring innovative targets for firm innovation following a downgrade.

The results are reported in Table 11. Interestingly, we find that an acquisition of innovative targets mitigates the decline in R&D expenditure and patent quality but not patent quantity following rating downgrades. The evidence implies technological synergies obtained from acquiring innovative firms and combining corporate innovation activities (see Sevilir and Tian, 2012; Bena and Li, 2014). Specifically, following sovereign downgrades, R&D expenditures remain largely unchanged among bound firms that acquire innovative targets. Furthermore, these firms seem to exploit the technology advantage of target firms and improve innovation quality rather than quantity, as evidenced by a significant reduction in patent applications and an insignificant change in patent citations.[13]

[Insert Table 11 about here]

7. Conclusion

In this paper, we investigate how credit ratings affect corporate innovation, by exploiting sovereign rating downgrades as an exogenous shock to the credit ratings of firms at the sovereign bound ex ante. Because of rating agencies' sovereign ceiling policy that requires firms' ratings not to surpass the sovereign rating of their country of domicile, the variation in corporate ratings of bound firms following a sovereign downgrade is unlikely an outcome of changes in firm fundamentals. This exogenous variation enables us to identify a causal effect of credit ratings on firm innovation activities. Based on this setting, we find robust evidence that a sovereign downgrade leads to significant reductions in R&D expenditures, patent applications and citations in bound firms, relative to non-bound firms.

We perform additional analyses and robustness checks and confirm that our findings are not driven by economic shocks. Also, our findings are unlikely to be due to differential exposure to the government's health between bound and non-bound firms. Moreover, we show that firms are similar in terms of innovation before sovereign downgrades, thereby validating the parallel trends assumption of our identification strategy.

To investigate the potential mechanism, we perform further tests showing that the effect of credit ratings on innovation is concentrated in firms that are more dependent on external finance.

[13] While these results point out the role of acquisitions in firm innovation at the time of rating downgrades, they should be viewed with caution due to the limited number of treated firms.

In addition, we find a shift in the debt structure of bound firms from public bonds towards bank loans as well as a significant increase in the use of covenants in the loans borrowed by bound firms in the event of sovereign downgrades. These results collectively suggest the increase in creditor control as the underlying mechanism through which rating downgrades impede firm innovation.

Furthermore, to enrich our understanding of how credit ratings affect various investment activities, we examine the effect of sovereign downgrades on M&A transactions. While our results imply insignificant changes in acquisition spending or frequency, we find that bound firms are more likely to acquire innovative targets following a sovereign downgrade. Also, we provide evidence that an acquisition of innovative targets mitigates the decline in R&D expenditure and patent quality following rating downgrades, suggesting that firms undertake M&As strategically to promote innovativeness.

Overall, this study sheds light on the link between credit ratings and the real economy. As innovation is an important catalyst for economic growth, by focusing on firm innovation, we provide new insights into the real effects of credit ratings on economic development.

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Table 1: Descriptive statistics

Panel A of this table reports summary statistics for variables constructed using a sample of public firms from 1995 to 2012. Innovation variables ($RDTA_{t+1}$, LN_PAT_{t+1}, and LN_CITE_{t+1}) are measured one year ahead (i.e., from 1996 to 2013). All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are in Appendix B. Panel B shows the changes in corporate ratings between bound and non-bound firms around sovereign downgrades. *NUMRATING* is the numerical scale S&P credit rating (from 1 for the lowest rating SD/D to 22 for the highest rating AAA). Robust standard errors clustered by country-event are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary statistics of variables

Variable	N	Mean	SD	p25	p50	p75
$BOUND\_DOWN_t$	10,490	0.004	0.062	0.000	0.000	0.000
$BOUND_{t-1}$	10,490	0.062	0.242	0.000	0.000	0.000
$DOWN_t$	10,490	0.070	0.255	0.000	0.000	0.000
$RDTA_{t+1}$	10,490	2.565	4.115	0.000	0.778	3.107
LN_PAT_{t+1}	10,490	1.586	1.971	0.000	0.693	2.996
LN_CITE_{t+1}	10,490	0.402	0.607	0.000	0.000	0.765
LN_AT_{t-1}	10,490	8.555	1.543	7.533	8.494	9.636
Q_{t-1}	10,490	1.651	0.965	1.082	1.353	1.834
LEV_{t-1}	10,490	0.288	0.179	0.168	0.273	0.383
$RDTA_{t-1}$	10,490	2.538	4.000	0.000	0.761	3.148
ROA_{t-1}	10,490	0.130	0.073	0.085	0.124	0.169
$PPETA_{t-1}$	10,490	0.336	0.213	0.166	0.291	0.480
$CAPEXTA_{t-1}$	10,490	0.056	0.042	0.027	0.045	0.072
$SAINDEX_{t-1}$	10,490	-3.983	0.488	-4.578	-3.917	-3.597
LN_AGE_{t-1}	10,490	2.984	0.765	2.565	2.944	3.714
LN_GDPPC_{t-1}	10,490	10.612	0.451	10.620	10.715	10.771
$GDPGROWTH_{t-1}$	10,490	2.262	2.310	1.528	2.667	3.796
$INFLATION_{t-1}$	10,490	2.086	1.566	1.421	2.298	2.931

Panel B: Changes in corporate ratings around sovereign downgrades

	NUMRATING		
	Year before sovereign downgrade	Year of sovereign downgrade	Difference
Bound firms	17.297	15.811	-1.486***
			(0.379)
Non-bound firms	9.670	9.618	-0.052
			(0.081)
Difference	7.627**	6.193**	-1.434***
	(2.764)	(2.654)	(0.357)

Table 2: Baseline regression results

This table shows OLS regression estimates of the effect of a sovereign downgrade on the innovation activities of firms that have a pre-downgrade rating at the sovereign bound (i.e., bound firms) relative to other firms. The dependent variables are research and development expenses scaled by total assets in year *t*+1 ($RDTA_{t+1}$), natural logarithm of one plus the number of patent applications filed in year *t*+1 (LN_PAT_{t+1}), and natural logarithm of one plus the average number of adjusted non-self-citations received on the patents filed in year *t*+1 (LN_CITE_{t+1}), respectively. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Y =	$RDTA_{t+1}$	LN_PAT_{t+1}	LN_CITE_{t+1}
	(1)	(2)	(3)
$BOUND\_DOWN_t$	-0.188**	-0.189***	-0.163***
	(0.072)	(0.058)	(0.052)
$BOUND_{t-1}$	0.008	0.228	0.032
	(0.099)	(0.174)	(0.043)
$DOWN_t$	0.057	0.032	0.073
	(0.053)	(0.063)	(0.044)
LN_AT_{t-1}	-0.133***	0.167***	0.055**
	(0.049)	(0.038)	(0.025)
Q_{t-1}	0.112***	0.074***	0.037***
	(0.038)	(0.018)	(0.005)
LEV_{t-1}	-0.471***	0.046	-0.028
	(0.102)	(0.093)	(0.047)
$RDTA_{t-1}$	0.332***	-0.000	-0.000
	(0.005)	(0.011)	(0.002)
ROA_{t-1}	0.282	0.677***	0.092
	(0.587)	(0.188)	(0.106)
$PPETA_{t-1}$	-0.172	0.002	0.019
	(0.267)	(0.237)	(0.089)
$CAPEXTA_{t-1}$	-1.299***	0.421	0.188
	(0.287)	(0.398)	(0.139)
$SAINDEX_{t-1}$	-0.624	-0.528***	-0.091
	(0.387)	(0.152)	(0.113)
LN_AGE_{t-1}	-0.092	0.057	0.030
	(0.178)	(0.072)	(0.032)
LN_GDPPC_{t-1}	1.644*	1.268	-0.016
	(0.889)	(1.344)	(0.438)
$GDPGROWTH_{t-1}$	-0.019*	0.013	-0.002
	(0.011)	(0.016)	(0.007)
$INFLATION_{t-1}$	0.001	-0.009	-0.007
	(0.013)	(0.016)	(0.009)
Constant	-16.923*	-16.187	-0.835
	(9.815)	(14.193)	(4.513)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	10,490	10,490	10,490
Adjusted R-squared	0.917	0.874	0.532

Table 3: Difference-in-differences (DiD) in innovation around a sovereign downgrade

This table reports DiD tests examining how sovereign downgrades affect firm innovation. Treated firms have a credit rating at the sovereign bound in the year before a sovereign downgrade. Control firms are matched firms using a nearest-neighbor matching algorithm. The matching covariates are industry, year, size, leverage, Tobin's Q, cash flow, research and development expenses, tangibility, external finance dependence, GDP growth, and inflation (pre-treatment values). The matched sample consists of 39 treated and control observations. Panel A compares the covariates between treated and control firms in the year before a sovereign downgrade. The *p*-values are from the *t*-test of difference in means and the Kolmogorov-Smirnov test of difference in distributions between treated and control firms, respectively. Panel B presents difference-in-differences estimators for innovation measures around a sovereign downgrade. Panel C presents difference-in-differences estimators for country-adjusted innovation measures. Robust standard errors clustered by country-event are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Characteristics of treated and control firms in the year before sovereign downgrades

Matching covariate	Mean		*t*-test *p*-value	Kolmogorov-Smirnov test *p*-value
	Treated firms	Control firms		
LN_AT_{t-1}	9.842	9.539	0.409	0.556
LEV_{t-1}	0.278	0.287	0.811	0.745
Q_{t-1}	1.856	1.733	0.710	1.000
CF_{t-1}	0.177	0.181	0.870	0.906
$RDTA_{t-1}$	1.726	2.033	0.674	0.556
$PPETA_{t-1}$	0.489	0.456	0.537	0.385
EFD_{t-1}	0.836	0.813	0.986	0.906
$GDPGROWTH_{t-1}$	2.956	3.022	0.905	0.745
$INFLATION_{t-1}$	1.944	1.435	0.409	0.250

Panel B: Difference-in-differences in innovation measures

	(1) *RDTA*			(2) *LN_PAT*			(3) *LN_CITE*		
	Year before downgrade	Year after downgrade	Difference	Year before downgrade	Year after downgrade	Difference	Year before downgrade	Year after downgrade	Difference
Treated firms	2.013	1.600	-0.413***	1.673	1.451	-0.222*	0.358	0.286	-0.072
			(0.141)			(0.114)			(0.098)
Control firms	1.925	2.055	0.130	2.096	2.264	0.167	0.604	0.688	0.084*
			(0.152)			(0.114)			(0.045)
Difference	0.088	-0.455***	**-0.543*** **	-0.423	-0.813	**-0.389** **	-0.246	-0.403***	**-0.157* **
	(0.170)	(0.124)	**(0.183)**	(0.450)	(0.526)	**(0.161)**	(0.143)	(0.138)	**(0.085)**

Panel C: Difference-in-differences in country-adjusted innovation measures

	(1) Country-adjusted *RDTA*			(2) Country-adjusted *LN_PAT*			(3) Country-adjusted *LN_CITE*		
	Year before downgrade	Year after downgrade	Difference	Year before downgrade	Year after downgrade	Difference	Year before downgrade	Year after downgrade	Difference
Treated firms	0.432	0.199	-0.233**	0.020	-0.035	-0.055	-0.023	-0.064	-0.042
			(0.099)			(0.085)			(0.096)
Control firms	-0.364	-0.245	0.119	0.291	0.434	0.144	0.177	0.257	0.080*
			(0.143)			(0.093)			(0.045)
Difference	0.796**	0.444	**-0.352** **	-0.271	-0.470	**-0.199* **	-0.199	-0.321**	**-0.122**
	(0.350)	(0.314)	**(0.133)**	(0.367)	(0.411)	**(0.111)**	(0.119)	(0.115)	**(0.085)**

Table 4: Robustness test with entropy balancing

This table shows regression estimates of the effect of a sovereign downgrade on the innovation activities of firms that have a pre-downgrade rating at the sovereign bound (i.e., bound firms) relative to other firms, by using the entropy balancing technique. Panel A reports the mean and variance of the covariates before and after balancing. In Panel B, we rerun the baseline regressions with the weights of observations obtained from entropy balancing. The dependent variables are research and development expenses scaled by total assets in year *t*+1 ($RDTA_{t+1}$), natural logarithm of one plus the number of patent applications filed in year *t*+1 (LN_PAT_{t+1}), and natural logarithm of one plus the average number of adjusted non-self-citations received on the patents filed in year *t*+1 (LN_CITE_{t+1}), respectively. Control variables (LN_AT_{t-1}, Q_{t-1}, LEV_{t-1}, $RDTA_{t-1}$, ROA_{t-1}, $PPETA_{t-1}$, $CAPEXTA_{t-1}$, $SAINDEX_{t-1}$, LN_AGE_{t-1}, LN_GDPPC_{t-1}, $GDPGROWTH_{t-1}$, and $INFLATION_{t-1}$) are untabulated for brevity. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Covariate balance before and after entropy balancing

	Pre-balancing				Post-balancing			
	Treated Mean	Nontreated Mean	Treated Variance	Nontreated Variance	Treated Mean	Nontreated Mean	Treated Variance	Nontreated Variance
LN_AT_{t-1}	9.764	8.565	3.042	2.381	9.764	9.764	3.042	3.042
LEV_{t-1}	0.283	0.289	0.030	0.032	0.283	0.283	0.030	0.030
Q_{t-1}	1.966	1.650	2.956	0.932	1.966	1.966	2.956	2.956
CF_{t-1}	0.177	0.144	0.007	0.008	0.177	0.177	0.007	0.007
$RDTA_{t-1}$	1.642	2.526	9.000	15.960	1.642	1.642	9.000	9.000
$PPETA_{t-1}$	0.485	0.338	0.051	0.046	0.485	0.485	0.051	0.051
EFD_{t-1}	0.761	0.145	33.260	15.970	0.761	0.761	33.260	33.260
$GDPGROWTH_{t-1}$	2.886	2.250	7.477	5.328	2.886	2.886	7.477	7.477
$INFLATION_{t-1}$	2.141	2.078	9.804	2.441	2.141	2.141	9.804	9.804

Panel B: Regression results by using entropy balancing

Y =	$RDTA_{t+1}$	LN_PAT_{t+1}	LN_CITE_{t+1}
	(1)	(2)	(3)
$BOUND\_DOWN_t$	-0.083**	-0.273***	-0.315***
	(0.035)	(0.073)	(0.070)
$BOUND_{t-1}$	0.090	0.098	-0.048
	(0.122)	(0.227)	(0.071)
$DOWN_t$	-0.012	0.065	0.353***
	(0.052)	(0.084)	(0.079)
Constant	-10.211**	-11.045*	-1.657
	(4.264)	(5.641)	(6.511)
Control variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	10,448	10,448	10,448
Adjusted R-squared	0.973	0.960	0.727

Table 5: Placebo tests

Panel A of this table shows OLS regression estimates of a placebo test on the effect of a sovereign downgrade in neighboring countries on the innovation activities of firms that have a rating at the sovereign bound ex ante (i.e., bound firms) relative to other firms. Panel B of this table shows OLS regression estimates of a placebo test on the effect of a sovereign downgrade on the innovation activities of firms with a rating one or two notches below the sovereign bound ex ante relative to firms with a rating more than two notches below the sovereign bound ex ante. Bound firms are excluded. Panel C of this table shows OLS regression estimates of a placebo test where we falsely assume that a country's first sovereign downgrade occurs three years before it actually does. The dependent variables are research and development expenses scaled by total assets in year *t*+1 ($RDTA_{t+1}$), natural logarithm of one plus the number of patent applications filed in year *t*+1 (LN_PAT_{t+1}), and natural logarithm of one plus the average number of adjusted non-self-citations received on the patents filed in year *t*+1 (LN_CITE_{t+1}), respectively. Control variables (LN_AT_{t-1}, Q_{t-1}, LEV_{t-1}, $RDTA_{t-1}$, ROA_{t-1}, $PPETA_{t-1}$, $CAPEXTA_{t-1}$, $SAINDEX_{t-1}$, LN_AGE_{t-1}, LN_GDPPC_{t-1}, $GDPGROWTH_{t-1}$, and $INFLATION_{t-1}$) are untabulated for brevity. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Placebo test using downgrades in neighboring countries

Y =	$RDTA_{t+1}$	LN_PAT_{t+1}	LN_CITE_{t+1}
	(1)	(2)	(3)
$BOUND\_NBDOWN_t$	0.004	0.123	0.052
	(0.070)	(0.089)	(0.046)
$BOUND_{t-1}$	-0.007	0.202	0.010
	(0.100)	(0.167)	(0.041)
$NBDOWN_t$	0.040	-0.022	0.018
	(0.046)	(0.040)	(0.022)
Constant	-16.415	-15.86	-0.210
	(9.832)	(13.999)	(4.286)
Control variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	10,490	10,490	10,490
Adjusted R-squared	0.917	0.874	0.531

Panel B: Placebo test examining possibly differential government exposure

Y =	$RDTA_{t+1}$	LN_PAT_{t+1}	LN_CITE_{t+1}
	(1)	(2)	(3)
$LBOUND\_DOWN_t$	0.093	-0.105	-0.066
	(0.058)	(0.133)	(0.059)
$LBOUND_{t-1}$	-0.067	0.089	0.017
	(0.118)	(0.107)	(0.032)
$DOWN_t$	0.047	0.026	0.049
	(0.064)	(0.079)	(0.036)
Constant	-8.737	-0.149	-4.306
	(8.761)	(16.847)	(4.774)

Control variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	9,836	9,836	9,836
Adjusted R-squared	0.917	0.869	0.513

Panel C: Placebo test changing the timing of downgrades

Y =	$RDTA_{t+1}$ (1)	LN_PAT_{t+1} (2)	LN_CITE_{t+1} (3)
$BOUND\_TDOWN_t$	-0.564	0.088	0.096
	(0.692)	(0.210)	(0.102)
$BOUND_{t-1}$	-0.002	0.216	0.015
	(0.101)	(0.173)	(0.044)
$TDOWN_t$	-0.108	-0.094*	-0.012
	(0.100)	(0.053)	(0.019)
Constant	-16.866*	-16.060	-0.223
	(9.669)	(13.908)	(4.354)
Control variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	10,490	10,490	10,490
Adjusted R-squared	0.917	0.874	0.531

Table 6: The effect of sovereign rating upgrades

This table shows OLS regression estimates of the effect of a sovereign upgrade on the innovation activities of firms that have a rating at the sovereign bound ex ante (i.e., bound firms) relative to other firms. The dependent variables are research and development expenses scaled by total assets in year *t*+1 ($RDTA_{t+1}$), natural logarithm of one plus the number of patent applications filed in year *t*+1 (LN_PAT_{t+1}), and natural logarithm of one plus the average number of adjusted non-self-citations received on the patents filed in year *t*+1 (LN_CITE_{t+1}), respectively. Control variables (LN_AT_{t-1}, Q_{t-1}, LEV_{t-1}, $RDTA_{t-1}$, ROA_{t-1}, $PPETA_{t-1}$, $CAPEXTA_{t-1}$, $SAINDEX_{t-1}$, LN_AGE_{t-1}, LN_GDPPC_{t-1}, $GDPGROWTH_{t-1}$, and $INFLATION_{t-1}$) are untabulated for brevity. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Y =	$RDTA_{t+1}$	LN_PAT_{t+1}	LN_CITE_{t+1}
	(1)	(2)	(3)
$BOUND\_UP_t$	0.005	-0.049	0.014
	(0.062)	(0.099)	(0.052)
$BOUND_{t-1}$	-0.005	0.233	0.014
	(0.102)	(0.189)	(0.049)
UP_t	-0.025	-0.043	-0.013
	(0.041)	(0.040)	(0.031)
Constant	-16.274	-15.292	-0.210
	(9.956)	(13.887)	(4.218)
Control variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	10,490	10,490	10,490
Adjusted R-squared	0.917	0.874	0.531

Table 7: Cross-sectional analysis based on dependence on external finance

This table shows the cross-sectional analysis on the effect of a sovereign downgrade on the innovation activities of firms that have a pre-downgrade rating at the sovereign bound (i.e., bound firms) relative to other firms. In Columns 1, 3, and 5, the regression sample is restricted to firm-year observations with external finance dependence that is above the annual median, while the sample in Columns 2, 4, and 6 is restricted to firm-year observations with external finance dependence below the annual median. External finance dependence is defined at the industry level, as the median of capital expenditures minus funds from operations, scaled by capital expenditures, among all the U.S. firms from Compustat in an industry-year (Rajan and Zingales, 1998). The dependent variables are research and development expenses scaled by total assets in year *t*+1 ($RDTA_{t+1}$), natural logarithm of one plus the number of patent applications filed in year *t*+1 (LN_PAT_{t+1}), and natural logarithm of one plus the average number of adjusted non-self-citations received on the patents filed in year *t*+1 (LN_CITE_{t+1}), respectively. Control variables (LN_AT_{t-1}, Q_{t-1}, LEV_{t-1}, $RDTA_{t-1}$, ROA_{t-1}, $PPETA_{t-1}$, $CAPEXTA_{t-1}$, $SAINDEX_{t-1}$, LN_AGE_{t-1}, LN_GDPPC_{t-1}, $GDPGROWTH_{t-1}$, and $INFLATION_{t-1}$) are untabulated for brevity. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Y =	$RDTA_{t+1}$		LN_PAT_{t+1}		LN_CITE_{t+1}	
	(1) High	(2) Low	(3) High	(4) Low	(5) High	(6) Low
$BOUND\_DOWN_t$	-0.200***	0.002	-0.243***	-0.006	-0.241***	-0.001
	(0.061)	(0.217)	(0.038)	(0.145)	(0.061)	(0.131)
$BOUND_{t-1}$	-0.025	0.019	0.353*	0.015	0.087	0.045
	(0.133)	(0.125)	(0.178)	(0.195)	(0.070)	(0.059)
$DOWN_t$	0.094	-0.107	-0.038	0.040	0.070*	0.073
	(0.095)	(0.138)	(0.067)	(0.105)	(0.041)	(0.073)
Constant	-27.604**	-8.357	-19.439*	-4.489	0.199	1.541
	(11.712)	(15.447)	(10.970)	(18.973)	(4.828)	(6.779)
Control variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	5,154	5,336	5,154	5,336	5,154	5,336
Adjusted R-squared	0.914	0.920	0.892	0.869	0.573	0.499

Table 8: Changes in capital structure around a sovereign downgrade

This table shows the effect of a sovereign downgrade on capital structure and debt choice of firms that have a pre-downgrade rating at the sovereign bound (i.e., bound firms) relative to other firms. The dependent variables are the ratio of total debt to total assets in year *t* (LEV_t), the ratio of long-term debt to total assets in year *t* ($LTLEV_t$), and the ratio of bank debt to total debt in year *t* ($BANKDEBT_t$), respectively. Control variables (LN_AT_{t-1}, Q_{t-1}, LEV_{t-1}, $RDTA_{t-1}$, ROA_{t-1}, $PPETA_{t-1}$, $CAPEXTA_{t-1}$, $SAINDEX_{t-1}$, LN_AGE_{t-1}, LN_GDPPC_{t-1}, $GDPGROWTH_{t-1}$, and $INFLATION_{t-1}$) are untabulated for brevity. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Y =	LEV_t	$LTLEV_t$	$BANKDEBT_t$
	(1)	(2)	(3)
$BOUND\_DOWN_t$	0.021	0.010	6.746***
	(0.018)	(0.009)	(2.120)
$BOUND_{t-1}$	-0.003	-0.001	-1.375
	(0.005)	(0.007)	(2.192)
$DOWN_t$	0.006	0.005	-1.875
	(0.003)	(0.004)	(1.224)
Constant	0.059	0.965*	-6.016
	(0.426)	(0.512)	(265.071)
Control variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	10,478	10,478	6,626
Adjusted R-squared	0.845	0.809	0.692

Table 9: Changes in covenant intensity around a sovereign downgrade

This table shows the effect of a sovereign downgrade on covenant intensity in loan agreements of firms that have a pre-downgrade rating at the sovereign bound (i.e., bound firms) relative to other firms. The dependent variables are the number of covenants in a loan issued in year *t* ($NUMCOVE_t$) and the average number of covenants in loans borrowed by a firm in year *t* ($AVGCOVE_t$), respectively. Control variables (LN_AT_{t-1}, Q_{t-1}, LEV_{t-1}, $RDTA_{t-1}$, ROA_{t-1}, $PPETA_{t-1}$, $CAPEXTA_{t-1}$, $SAINDEX_{t-1}$, LN_AGE_{t-1}, LN_GDPPC_{t-1}, $GDPGROWTH_{t-1}$, and $INFLATION_{t-1}$) are untabulated for brevity. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Y =	$NUMCOVE_t$ (1) Loan level	$AVGCOVE_t$ (2) Firm level
$BOUND\_DOWN_t$	0.189**	0.160**
	(0.092)	(0.078)
$BOUND_{t-1}$	-0.051	-0.103
	(0.052)	(0.061)
$DOWN_t$	0.002	0.023
	(0.033)	(0.033)
Constant	-3.211	-5.538
	(7.252)	(10.920)
Control variables	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
N	7,361	4,891
Adjusted R-squared	0.439	0.475

Table 10: Changes in merger and acquisition transactions around a sovereign downgrade

This table shows the effect of a sovereign downgrade on merger and acquisition transactions of firms that have a pre-downgrade rating at the sovereign bound (i.e., bound firms) relative to other firms. The dependent variables are the firm-level total dollar amount spent on acquisitions in year *t*+1 ($ACQVALUE_{t+1}$), the total number of acquisitions made by a firm in year *t*+1 ($ACQNUM_{t+1}$), and the deal-level indicator variable that equals one if the target firm has filed at least one patent application in the past five years ($INNOVT_{t+1}$), respectively. Control variables (LN_AT_{t-1}, Q_{t-1}, LEV_{t-1}, $RDTA_{t-1}$, ROA_{t-1}, $PPETA_{t-1}$, $CAPEXTA_{t-1}$, $SAINDEX_{t-1}$, LN_AGE_{t-1}, LN_GDPPC_{t-1}, $GDPGROWTH_{t-1}$, and $INFLATION_{t-1}$) are untabulated for brevity. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Y =	$ACQVALUE_{t+1}$	$ACQNUM_{t+1}$	$INNOVT_{t+1}$
	(1) Firm level	(2) Firm level	(3) Deal level
$BOUND\_DOWN_t$	-0.006	0.019	0.164***
	(0.009)	(0.164)	(0.042)
$BOUND_{t-1}$	-0.008	-0.015	-0.016
	(0.009)	(0.138)	(0.029)
$DOWN_t$	0.003*	-0.030	-0.016
	(0.002)	(0.055)	(0.040)
$DIVERS_{t+1}$			-0.065***
			(0.006)
$HOSTILE_{t+1}$			-0.027
			(0.050)
IMA_{t+1}			-0.114***
			(0.012)
$STOCK_{t+1}$			0.013
			(0.010)
$PUBT_{t+1}$			0.170***
			(0.009)
Constant	-0.631	-6.247	-1.425
	(0.529)	(6.001)	(1.992)
Control variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	10,490	10,490	4,585
Adjusted R-squared	0.134	0.288	0.216

Table 11: The effect of an acquisition of innovative targets

This table shows OLS regression estimates of the effect of acquisitions of innovative targets after a sovereign downgrade on the innovation activities of firms that have a pre-downgrade rating at the sovereign bound (i.e., bound firms) relative to other firms. The dependent variables are research and development expenses scaled by total assets from year *t*+1 to year *t*+3 ($RDTA_{t+1\sim t+3}$), natural logarithm of one plus the number of patent applications filed in year *t*+1 to year *t*+3 ($LN\_PAT_{t+1\sim t+3}$), and natural logarithm of one plus the average number of adjusted non-self-citations received on the patents filed in year *t*+1 to year *t*+3 ($LN\_CITE_{t+1\sim t+3}$), respectively. Control variables (LN_AT_{t-1}, Q_{t-1}, LEV_{t-1}, $RDTA_{t-1}$, ROA_{t-1}, $PPETA_{t-1}$, $CAPEXTA_{t-1}$, $SAINDEX_{t-1}$, LN_AGE_{t-1}, LN_GDPPC_{t-1}, $GDPGROWTH_{t-1}$, and $INFLATION_{t-1}$) are untabulated for brevity. Variable definitions are provided in Appendix B. Robust standard errors clustered by country are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Y =	$RDTA_{t+1\sim t+3}$	$LN\_PAT_{t+1\sim t+3}$	$LN\_CITE_{t+1\sim t+3}$
	(1)	(2)	(3)
$BOUND\_DOWN_t$	-0.214**	-0.243***	-0.144***
	(0.100)	(0.079)	(0.051)
$BOUND_{t-1}$	0.036	0.220	0.043
	(0.121)	(0.159)	(0.051)
$DOWN_t$	0.061	0.028	0.063*
	(0.048)	(0.063)	(0.036)
$BOUND\_DOWN_t \times NUMINNOVT_{t+1}$	0.169**	-0.063	0.174***
	(0.082)	(0.044)	(0.048)
$BOUND_{t-1} \times NUMINNOVT_{t+1}$	0.086	0.002	-0.017
	(0.054)	(0.048)	(0.020)
$DOWN_t \times NUMINNOVT_{t+1}$	-0.194**	0.092***	-0.052**
	(0.095)	(0.027)	(0.022)
$NUMINNOVT_{t+1}$	0.036	0.030*	0.035***
	(0.047)	(0.016)	(0.009)
Constant	-20.008*	-12.631	0.610
	(11.371)	(11.889)	(5.346)
Control variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	10,490	10,490	10,490
Adjusted R-squared	0.942	0.912	0.660

Appendix A: The sample of sovereign rating downgrades and affected firm-years

Country	Downgrade year	Sovereign rating before downgrade	Sovereign rating after downgrade	Number of treated firms	Company name
Argentina	2000	BB	BB-	1	YPF S.A.
	2001	BB-	SD	1	YPF S.A.
	2008	B+	B-	1	YPF S.A.
Brazil	1999	BB-	B+	4	Ampla Energia e Servicos S.A
					Sadia S.A.
					Bunge Alimentos S.A.
					Aracruz Celulose S.A.
	2002	BB-	B+	3	Ampla Energia e Servicos S.A
					Sadia S.A.
					Aracruz Celulose S.A.
Hungary	2012	BB+	BB	1	MOL Hungarian Oil and Gas PLC
Indonesia	1997	BBB	BB+	1	PT Hanjaya Mandala Sampoerna Tbk.
	1998	BB+	CCC+	1	PT Hanjaya Mandala Sampoerna Tbk.
Italy	2004	AA	AA-	1	Eni SpA
	2006	AA-	A+	1	Eni SpA
	2011	A+	A	1	Eni SpA
	2012	A	BBB+	1	Eni SpA
Japan	2001	AAA	AA	1	Toyota Motor Corp.
	2002	AA	AA-	2	Denso Corp.
					Toyota Motor Corp.
	2011	AA	AA-	12	Nippon Telegraph & Telephone Corp.
					Denso Corp.
					Takeda Pharmaceutical Co. Ltd.
					Chubu Electric Power Co. Inc.
					Tokyo Electric Power Co. Inc.
					Tokyo Gas Co. Ltd.
					Shikoku Electric Power Co. Inc.
					Canon Inc.
					Electric Power Development Co. Ltd.
					Toyota Motor Corp.
					NTT DOCOMO Inc.
					Osaka Gas Co. Ltd.
Korea	1997	AA-	B+	1	Korea Electric Power Corp.
Mexico	2009	BBB+	BBB	2	Grupo Bimbo S.A.B. de C.V.
					Grupo Televisa S.A.B.
Malaysia	1997	A+	A	1	Telekom Malaysia Bhd.

	1998	A	BBB-	1	Telekom Malaysia Bhd.
Turkey	2001	B+	B-	1	Vestel Elektronik Sanayi Ve Ticaret A.S.
Taiwan	2002	AA	AA-	1	Chunghwa Telecom Co. Ltd.
United States	2011	AAA	AA+	2	Johnson & Johnson
					Microsoft Corp.

Appendix B: Variable definitions

Variable	Definition
RDTA	Research and development expenditures divided by book value of total assets, multiplied by 100, and set to zero if missing.
LN_PAT	Natural logarithm of one plus the number of patent applications filed in a year.
LN_CITE	Natural logarithm of one plus the average number of adjusted non-self-citations received on the patents filed in a year. For each patent, its adjusted citations are computed based on technology class (IPC1) issued by the European Patent Office as the number of subsequent citations received on this patent divided by the average number of subsequent citations received on all patents categorized in the same technology class and filed in the same year as the focal patent.
BOUND	An indicator variable that is equal to one if a firm has a credit rating at the sovereign bound and zero otherwise.
DOWN	An indicator variable that is equal to one if a sovereign downgrade occurs and zero otherwise.
BOUND_DOWN	An indicator variable that is equal to one if a firm's country rating is downgraded and the firm has a rating at the sovereign bound before the sovereign downgrade and zero otherwise.
NBDOWN	An indicator variable that is equal to one if a firm's country is not downgraded but at least one neighboring country is downgraded and zero otherwise.
BOUND_NBDOWN	An indicator variable that is equal to one if a firm's country is defined as experiencing a placebo downgrade (i.e., *NBDOWN*=1) and the firm has a rating at the sovereign bound before the placebo downgrade and zero otherwise.
LBOUND	An indicator variable that is equal to one for firms with a credit rating one or two notches below the sovereign bound and zero for firms with a rating more than two notches below the sovereign bound.
LBOUND_DOWN	An indicator variable that is equal to one if a firm's country rating is downgraded and the firm has a rating one or two notches below the sovereign bound before the sovereign downgrade and zero otherwise.
TDOWN	An indicator variable that is equal to one if a firm's country is downgraded for the first time in year t+3 and zero otherwise.
BOUND_TDOWN	An indicator variable that is equal to one if a firm's country is downgraded for the first time in year t+3 (i.e., *TDOWN*=1) and the firm has a rating at the sovereign bound ex ante and zero otherwise.
UP	An indicator variable that is equal to one if a sovereign upgrade occurs and zero otherwise.
BOUND_UP	An indicator variable that is equal to one if a firm's country rating is upgraded and the firm has a rating at the sovereign bound before the sovereign upgrade and zero otherwise.
LN_AT	Natural logarithm of book value of total assets.
Q	Market-to-book ratio, computed as market value of equity plus book value of total assets minus book value of equity minus balance sheet deferred taxes (set to zero if missing) divided by book value of total assets.
LEV	Leverage ratio, computed as book value of total debt divided by book value of total assets.

ROA	Return on assets, computed as operating income before depreciation divided by book value of total assets.
PPETA	Tangibility, computed as net property, plant, and equipment divided by book value of total assets.
CAPEXTA	Capital expenditures scaled by book value of total assets.
SAINDEX	SA index developed by Hadlock and Pierce (2010), calculated as: $(-0.737\times\text{Size}) + (0.043\times\text{Size}^2) - (0.040\times\text{Age})$, where *Size* is the natural logarithm of total assets, and *Age* is the number of years the firm has been on Compustat with a non-missing stock price. *Size* is winsorized at the natural logarithm of $4.5 billion and *Age* is winsorized at thirty-seven years.
LN_AGE	Natural logarithm of one plus firm age, approximated by the number of years listed on Compustat.
LN_GDPPC	Natural logarithm of GDP per capita in constant 2010 US dollars.
GDPGROWTH	GDP annual growth rate in percentage.
INFLATION	Annual inflation rate in percentage.
CF	Cash flow scaled by lagged total assets.
EFD	External finance dependence, computed as the median of capital expenditures minus funds from operations (scaled by capital expenditures) among all public U.S. firms from Compustat in a firm’s three-digit SIC industry in a year.
LTLEV	The ratio of long-term debt to total assets.
BANKDEBT	The ratio of bank debt to total debt.
NUMCOVE	The number of covenants in a loan.
AVGCOVE	The average number of covenants in loans borrowed by a firm in a year.
ACQVALUE	The total dollar amount spent on acquisitions scaled by lagged total assets in a year.
ACQNUM	The number of acquisitions undertaken by a firm in a year.
INNOVT	An indicator variable that is equal to one if the target firm in an acquisition is innovative and zero otherwise. A target firm is defined as innovative if it has filed at least one patent application in the past five years.
DIVERS	An indicator variable that is equal to one if the acquirer and the target in a deal are from different two-digit SIC industries and zero otherwise.
HOSTILE	An indicator variable that is equal to one for hostile deals and zero otherwise.
IMA	An indicator variable that is equal to one for international mergers and zero otherwise.
STOCK	An indicator variable that is equal to one if a deal is at least partially financed by stock and zero otherwise.
PUBT	An indicator variable that is equal to one if the target firm in a deal is public and zero otherwise.
NUMINNOVT	The number of innovative targets acquired by a firm in a year. A target firm is defined as innovative if it has filed at least one patent application in the past five years.