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Why do insurers fail? A comparison of life and nonlife insurance companies from an international database

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Abstract

This paper tests the claim that insurers often engage in risk-shifting years before the materialization of a failure. It compares the mechanisms of insurance insolvency across different jurisdictions, using a first-of-its-kind international database assembled by the authors, merging individual financial data together with information on impairments over the last 30 years in four of the largest insurance markets in the world (France, Japan, the UK, and the United States). Results show evidence that low profitability is a leading indicator of failures. Further, there is an asymmetry between life insurance, where bond investment is highly significant, and nonlife insurance sectors, where operating inefficiency plays a larger role. Moreover, this paper highlights differences across countries: a stronger reaction to operating inefficiency in nonlife insurance in France and a less positive impact of bond investment in life insurance in Japan. Both results are linked to differences in the functioning of insurance markets.

KEYWORDS

comparison across countries, financial crises, insolvency prediction, insurance default

JEL CLASSIFICATION

G22, G01, G11

1 | INTRODUCTION

As highlighted in Plantin and Rochet (2007), the failure of insurance companies often takes place due to bad decision-making—ranging from negligent to fraudulent—several years preceding an actual failure. This issue, which stems from the so-called "inversion of the production cycle" in insurance (whereby firms collect premiums in advance of the realization of risks and the disbursement of funds to customers), is problematic from a supervisory point of view. Indeed, when insurers do fail, insolvency is quite costly; the resolution of an insurance company is 3–5 times more expensive than that of other financial institutions (Grace et al., 2003). Are there differences across countries in terms of supervisors' ability to identify doomed insurers before it is too late?

While historically less exposed to systemic crises, it was an insurer (AIG) who was at the center of a $200 billion rescue package from the United States government in the immediate aftermath of the 2007–2008 financial crisis. Additionally, Dutch insurer Aegon required a $3.7 billion bailout from its government during the same period, while a dangerous wave of life insurance failures helped magnify financial shocks in Japan following the Lost Decade. Today, the question of insurance insolvency has regained relevance as undertakings face increased pressure and uncertainty in the low (or negative) interest rate environment. The International Association of Insurance Supervisors (IAIS) has continued its pursuit of a formula for the identification of Globally Systemically Important Insurers (G-SIIs); new methodologies were released in 2013 and 2016 (IAIS, 2016). Further, the emergence of new threats from climate change, which is projected to increase the frequency and severity of extreme weather events,[1] has captured the attention of insurers and policymakers within the financial system. Still, the debate surrounding the systemic contribution of insurance remains open. Harrington (2009) emphasizes the lack of systemic footprint in traditional insurance activities, while Mühlnickel and Weiß (2015) demonstrate the systemic significance of mergers, nontraditional financing activities, and business-line diversification. While insurance liabilities are less "runnable" compared with banking, insurance risks do nonetheless exhibit some correlation with economic cycles. In the property and casualty (PC) sector, risk protection decreases during recessions, potentially driving up claims from policyholders. In the life insurance sector, surrenders are affected by the macroeconomic environment (Geneva Association, 2012), increasing during adverse economic conditions (the emergency fund theory relates surrenders to higher unemployment). In addition, upward shocks to long-term interest rates lead policyholders to look for higher alternative returns at times where insurers themselves face capital losses on their fixed-income portfolios. In the presence of such behavior, microprudential intervention becomes more important to help prevent contagion effects from spreading across firms.

In 2018, the European Insurance and Occupational Pensions Authority (EIOPA) published a study (EIOPA, 2018) which utilizes questionnaire survey responses from 31 national supervisory authorities to understand the presumed cause of 180 cases of fragility or "near-misses" in different European jurisdictions. The mostly qualitative work documents how, in the nonlife sector, the top declared risks involve the evaluation of technical provisions, corporate governance, and management. In the life sector, the top three reported risks are management, investment risk, and market risk—in line with the literature's emphasis on the linkages between life insurance and financial markets. Most events occur during or after the financial crisis of 2007–2008. Only 48% of cases represent failed firms, including firms that have been partially resolved.

[1]Several insurance defaults have been associated with natural catastrophes, such as Hurricane Andrew in the United States in 1992.

In addition, in the academic and policy debate, very few papers investigate to what extent regulatory frameworks over the world may explain certain differences in terms of insurance insolvencies. While US insolvencies are well documented, the question remains less studied outside of the United States and when monographs are available on certain jurisdictions, either actual defaults are unknown and the explained variable is the solvency ratio (e.g., Rauch & Wende, 2015 for Germany, and Chen & Wong, 2004 for Asia) or they fail to compare with other regions (Eling & Jia, 2018 concentrate on the EU only).

An important contribution of this paper is the construction of an international database of insurance failures, to which we apply several empirical strategies and provide some explanations for differences across countries. Our database is larger than those produced by the insurance insolvency prediction literature. EIOPA (2018) contains 180 EU cases from 1999 to 2016, while Leverty and Grace (2012) contain 256 US cases from 1989 to 2000. In comparison, our database includes 437 impairment cases in four big countries (France, Japan, the UK, and the United States). Eling and Jia (2018) use a large insolvency database composed of both life and nonlife insurers, but concentrate on Europe and include several small countries with specific insurance systems (Denmark, Ireland, etc.). We use our database to test a certain number of hypotheses on how these events take place, which helps predict future insurance failures on the basis of available financial data, highlighting similarities and differences between countries.

In this paper, we investigate several dynamics and intuitions provided by previous literature, including some case studies, regarding the relative importance of the asset and liability sides of an insurer's balance sheet for the sake of forecasting its default—and how this changes across sectors and countries. We additionally contribute to the evaluation of the potential impact of supervision, in the sense that we measure the true predictive power of the indicators collected by supervisors vis-à-vis future defaults. We find evidence that while such indicators matter, their predictive power changes depending on the nature of the business at hand, and the country in which a firm operates.

In addition to the construction of our database, the second major contribution of this paper to the literature is to confirm practitioners' and supervisors' view—which had never been clearly verified by the academic literature for failure prediction in insurance—that life and nonlife sectors behave very differently, with portfolio choice having an important impact for life and operating inefficiency in nonlife. We are able to better highlight these differences by separating analysis by sector using a single, common database. Further, we find that macroeconomic variables do not play a very significant role in determining insolvency. The significance of determinants, moreover, varies across jurisdictions: operating inefficiency appears more critical in French jurisdiction, while the asset composition (debt instruments) did not afford the same protection as elsewhere with respect to Japanese insurance failures.

Finally, we acknowledge that many different types of behavior may explain insolvencies. Nonetheless, investors and supervisors alike must condition their decision-making on available financial reporting. Seminal academic work such as Altman (1968) and Shumway (2001) precisely attempts to shed light on how simple financial ratios can be used by such parties. Applying this empirical approach to insurance, we seek to use historical data to help understand the following questions:

- While the years directly preceding an insurance impairment will see lower net income levels, do losses occur suddenly (through, i.e., a sudden spike in claims) or instead to they occur more gradually through time?

- What is the relative weight of macroeconomic determinants in insurance failures, as opposed to purely idiosyncratic, firm-level characteristics?
- While an increase in premiums by an insurer may be a sign of better performance, increasing market shares may also reveal underpricing or "gambling for resurrection" for a low profitability firm. Do failing firms experience a spike in premiums prior to collapse?
- What is the relationship between reinsurance ceded and the stability of equity/own funds? Without knowing detailed information about reinsurance treaties, do ceded premiums lower the volatility of net income relative to written premiums, or may it create reinsurance risk due to the complexity of the arrangements?
- Governance problems within insurance firms are often mentioned as a major source of insolvencies, and (as discussed below) various estimation techniques are used in the literature to capture a firm's operating inefficiency. Financial supervisors, however, typically concentrate on simple ratios. Can operating and administrative expenses capture a firm's governance quality?
- How do insolvency determinants vary according to a country's institutional or jurisdictional framework?

The remainder of this paper is organized as follows: Section 2 reviews the existing literature, Section 4 presents the novel data set and some summary statistics, and Section 5 outlines our expected results. Section 6 details our econometric approaches and expected results. Section 7 reports our results and robustness checks, and Section 8 concludes.

2 | REVIEW OF THE LITERATURE

The early insurance insolvency literature dealt mainly with the predictive performance of regulatory ratios and ratings. Ambrose and Seward (1988) use a multivariate linear discriminant analysis approach in which A. M. Best ratings are combined with the information given by financial statements. The authors find significant predictive power in the premiums-to-surplus ratio, the loss ratio, and time spent settling claims; the expense ratio, return on equity (ROE) (or, in some jurisdictions, "surplus" for insurers), and return on assets (ROA) were not significant predictors. Cummins et al. (1995) document the inadequacy of National Association of Insurance Commissioners (NAIC) RBC ratios, finding predictive power "very low" without additional regressors. Cummins et al. (1999) later compare the accuracy of the next generation of indicators—NAIC's so-called Financial Analysis and Surveillance Tracking (FAST) audit ratio system—with the classic risk-based capital (RBC) prudential measures. The authors find that while the "FAST" system dominates RBC ratios, predictive power remains low overall without additional inputs.

The more recent literature on insurance insolvency is related to four considerations: (i) efficient management and corporate governance, (ii) industrial organization, (iii) the macroeconomic environment, risk appetite, and portfolio choices, and (iv) profitability. We review the literature in each area.

First, different measures of "efficiency" or management quality have been proposed by academic studies. Leadbetter and Dibra (2008) show that management quality and risk appetite have been responsible for Canadian property–casualty insolvencies, although the authors posit that an adverse macroeconomic environment is often what pushes a company over the edge. Leverty and Grace (2010) examine two methods for measuring output in property-liability insurer efficiency studies. The authors find that efficient "value-added approach" firms are less likely to go insolvent, while firms characterized as efficient by the "flow" approach are generally more likely to fail. In a later study, Leverty and Grace (2012) find the managerial ability of CEOs to be inversely related to the amount of time a firm spends in distress, the likelihood of a firm's failure, and the cost of failure. Zhang and Nielson (2015) incorporate state-specific factors on a US database of property–casualty failures, finding that insurers with low business-line diversification, fewer failed Insurance Regulatory Information System ratio tests and membership in a larger group are less likely to become insolvent. Most recently, Eling and Jia (2018) show how "technical efficiency" is associated with financial health across the entire European sector.

Second, market structure is shown to matter. The earlier literature focused on a possible tradeoff between competition and financial stability, arguing that less market concentration (increased competition) increased the occurrence of firm failure, particularly in the nonlife industry. Browne and Hoyt (1995) find nonlife insolvency to be significantly tied to low market concentration—more insurers lead to slimmer margins and more failures—and further estimate the industrywide combined ratio to have predictive power for insolvency. EIOPA (2018) documents a similar trend: most detections of nonlife insolvency are small firms with low market share, which, the authors point out, mirrors the structure of the EU insurance market. In contrast, the more recent literature, notably Cummins et al. (2017), shows how increased competition throughout the EU pushes firms towards greater efficiency, improving the financial health of the sector. Zhang and Nielson (2015) also argue that highly concentrated insurers exhibit higher insolvency risk. Studying the period 1994–2008, Cheng and Weiss (2012) show that insolvencies in the property-liability insurance industry are positively correlated to the industrywide Herfindahl index of premiums written. This is consistent with the "quite life hypothesis" (Inoue, 2018) where firms do not maximize profits or minimize costs in less competitive environments. Similarly, Panzar–Rosse analysis (see Shaffer & Spierdijk, 2015) often used in banking which tends to show that, unlike competitive firms which are able to protect profits by increasing prices when costs are rising, less competitive markets respond more slowly, implying profits may be more sensitive to any shocks on costs that would magnify their inefficiencies, leading to an increase in insolvencies. We will later investigate to what extent insolvencies may be higher in more concentrated hence less competitive insurance markets.

Third, the health of insurance companies often fluctuates with the macroeconomic environment. The life insurance industry is widely understood to exhibit more interconnection with the macroeconomy, depending on the degree of liquidity of liabilities and the subsequent financial nature of the business. A 37% of life insurers in EIOPA's 17-year study experienced their failure or near-miss in the 2007–2008 window (EIOPA, 2018). Browne et al. (1999) show how life insurers are sensitive to long-term interest rates, personal income, unemployment, stock markets, and also the number of insurers present in the industry. In addition to firm size, Chen and Wong (2004) find asset returns to be a high-ranking factor explaining insurance company distress in both life and nonlife sectors of the Asian insurance market. Unlike property–casualty insurance, however, life policyholders may be able to withdraw funds to invest elsewhere. Kim (2005) explains surrender as a function of several economic variables, finding that increases in the interest rate often lead to disintermediation.[2] Unemployment, gross domestic product (GDP) growth rates, seasonal effects, and policy age appear important as well. Cheng and Weiss (2012) analyze the macroeconomic factors involved in nonlife insolvency, ultimately reaffirming the relevance of interest rate changes and market concentration. Russell et al. (2013) also test the sensitivity of life insurance surrender to

[2]Interestingly, in recent years, policyholders' sensitivity to the interest rate has seemed to diminish, implying substantial inertia in savers' behavior.

macroeconomic variables, finding a positive correlation between interest rate levels and a negative relation between income levels and interest rate spreads.

Connected to that, several papers show that insurance portfolio choices matter. Existing literature stresses the role of changes in asset mix for defaulting undertakings, linked to attempt to escape from difficulties by reshuffling assets (see, e.g., Carson & Hoyt, 1995). However, investment structure also plays a role—in particular, investing in less volatile assets such as sovereign or corporate bonds is likely to reduce the risk of insolvency. This is in line with insurance regulation designed to protect insurance policyholders. Lee and Urrutia (1996) find that the ratio of the market value of invested bonds to total admitted assets is a significant variable to predict nonlife insurance insolvency in 1980–1991. Similarly, using P/C insurers' insolvency data from 1998 to 2008, Zhang and Nielson (2015) document that the share of assets invested in bonds is significantly lower for firms which eventually experience insolvency.

Fourth and finally, the link between profitability and failure has been addressed by several authors in the literature. Eling and Jia (2018) show how, while ROE is weakly associated with health, its volatility positively correlates with the probability of failure. Bernard et al. (2016) use internal firm-level data from the French Prudential Supervision Authority (ACPR) to derive leading indicators of insurance distress. Although the econometric analysis yields few significant results, low levels of reserves and weak profitability appear to precede financial vulnerability.

3 | JURISDICTIONAL AND INSTITUTIONAL HETEROGENEITY

The database allows us to investigate to what extent insurance company insolvencies may have different determinants across countries. Several factors can help explain this phenomenon: the legal environment regarding insolvency, supervisory activism, market structure, and finally differences in contract-level guarantees.

Regarding the first dimension, insolvency regulations may differ across countries, and especially in the insurance industry as many such companies often receive a special treatment because of the sector's regulated status and the importance of insurance to the rest of the economy. First, insolvency procedures can include out-of-court arrangements, which often remain confidential but are common in the UK and in the United States. Second, they may involve proceedings under the supervision of courts, including so-called rehabilitation (notably in the United States and Japan, as well as administration in the UK, and so-called “redressement judiciaire” in France). Finally, a firm can enter liquidation. Court decisions across countries may strike a different balance between the different stakeholders, however: while the UK is more creditor friendly, France and Japan are debtor friendly, with the United States somewhere in the middle (see Asai, 2021; Beale & Bromley-White, 2021; Gumpelson & Dubois, 2021; Kornberg & McColm, 2021). This is also consistent with the view that some countries like the UK or the United States might be less reluctant to allow insurance firms to fail than in continental Europe and Japan (see Eling & Jia, 2018 for the EU).

Regarding the second dimension, continental European countries often experience more prudential activism from public authorities, which attempt to alleviate market pressures, while the UK has a more market-oriented approach which is more protective of policyholders. Overall, such factors may be indistinguishable from the previous dimension discussed above. Ultimately, the hypothesis to test for both cases is therefore whether economic determinants may have more explanatory power to predict insolvencies in the

United States and the UK than in France and Japan. In the empirical analysis, we test the role of shocks on firms' profits to predict insolvencies. Note, however, a possible caveat, in the sense that market-oriented countries may undergo more out-of-court settlements, so that the insolvencies defined by court proceedings or regulatory intervention may result from market failures. A detailed analysis of asset transfers by insurers close to insolvency would overcome this issue, but is beyond the scope of the current article.

The theoretical underpinnings of our approach of insurance failures are "insurance ruin theory," as explained by Plantin and Rochet (2007), which leads to imposing capital requirements to ensure that equity E is large enough to cover losses. According to such an analysis failure occurs if $A_0 + A_1(1 + r) < R(1 + x)$, where A_0 is a riskless asset. A_1 is a risky asset in which the insurer also invests the premiums collected, with stochastic return r and σ_r^2 is the standard deviation of the return on the risky assets held by the insurer, R the amount of reserves or technical provisions and σ_x^2, the standard deviation on the unit cost (actuarial losses) for the insurer (as a percentage of reserves, which measure to what extent initial reserves may diverge from the ex ante assessment). Given the balance sheet constraint $A_0 + A_1 = R + E$, failure occurs when net operating profit $A_1 r - Rx$ is such that $A_1 r - Rx < -E$.

We extend this framework by considering that insurers face additional management costs c, which are also stochastic, with standard deviation σ_c^2, while x is now defined as the loss payment. Failure now occurs if $A_0 + A_1(1 + r) < R(1 + x + c)$. If net operating profit is normally distributed, and r and c are assumed to be independent, failure will occur with a probability of less than 1% if Capital Requirements ensure that equity E is such that $E \geq 2\sqrt{A_1^2\sigma_r^2 + R^2(\sigma_x^2 + \sigma_c^2)}$.

Management costs c depend on the ability of the insurer to minimize costs. Following Cummins et al. (2017), we consider that regulation or the lack of competition prevents insurers from reaping the benefits of scale economies, hence increases unit costs. Higher regulation implies a shift to the right of the distribution of c, or an increase in σ_c^2. It may also imply a shift to the right of the distribution of x. To get an empirical counterpart of c, one can, for example, refer to OECD data (see OECD, 2021) to compute the ratio of Gross operating expenditures/Gross premiums. It turns out that it is systematically higher in nonlife insurance than that in life insurance, by 7–15 percentage points (pp) for each country, providing evidence that efficiency in the management of fees and claims is more important in nonlife insurance, while returns on investment matter more for life insurance.[3] Another reason why such an indicator would matter more for nonlife than life and weigh on profitability is typically the shorter contract structure and shorter liability duration in nonlife insurance. Finally, the use of book accounting notably in Japan, as opposed to fair-value accounting that may explain why market signals may be less effective for failure prediction. In particular, Fulcher and Kaplan (2013) note that "due to book accounting most of the insolvent insurers in the late 1990s and early 2000s were actually reporting profits and declaring dividends in the period immediately prior to their failure."

A first hypothesis to test is the following:

Hypothesis 1 – *ROA provides a better signal of insolvencies in more market-oriented countries.*

The third insolvency dimension mentioned above—market structure—may also imply differences in terms of the response of insolvencies. Specifically, the different countries under

[3]Data from the authors are available upon request.

study exhibit clear differences in terms of market concentration. As shown in Figure 1, the Herfindal–Hirschman Index is bigger in France than in the three other countries, providing evidence of a less competitive environment. This figure reflects the distribution of gross premiums across a given country's market in a given year. As discussed above, in line with the analysis conducted in Shaffer and Spierdijk (2015), we test the hypothesis that a shock on an insurance firm's costs has a larger effect on insolvencies in less competitive environments (namely, in France or Japan, vs. in the United States) and notably in nonlife insurance. Beyond the management of operations on which we focus here, and considering risk management, less competition may increase the risk of adverse selection, while we acknowledge that higher market power may also allow firms to exclude higher risks.

Hypothesis 2 – *Shocks to operating inefficiency matter more for insolvencies in countries where insurance markets are less competitive.*

The last dimension addressed above is product differentiation. While investing in less volatile assets like bonds is likely to reduce P/C insolvencies (Lee & Urrutia, 1996; Zhang & Nielson, 2015) the question explored here is whether it may hold for life insurance as well and similarly across national jurisdictions. However, the determinants of insurance failures in Japan appear to be more complex than in other countries. First, using OECD data, Gründl and Gal (2017) show that countries differ markedly: The share of insurance assets invested in bonds is lower in Asia than that in Europe and the United States. OECD (2021) indicates that the share of bonds in total investments in life insurance companies is more than 85% in the United States, between 65% and 75% in France, and between 40% and 65% in Japan in the 1990s. Jawadi et al. (2009) mention that the regulation may have forced Japanese insurers to hold equities. UK life insurers exhibit a lower share of bond investments as they often act as pension funds. Second, different scholars argue that financial regulation was rather lax in Japan in the 1990s, leading to the creation of the financial services agency in 1997. Third, many Japanese insurance failures took place in the wake of a major systemic crisis, following the collapse of the equity and real estate bubble, in the sense that the role of the financial system was impaired, preventing it to allocate funds properly. Fourth, as described by Bernard and

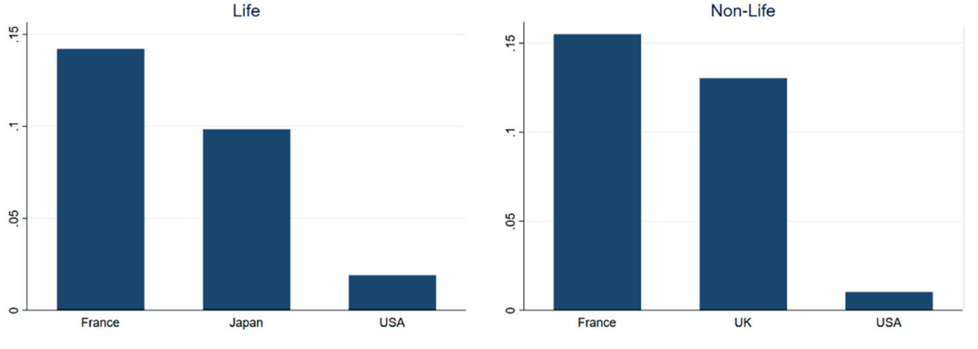

FIGURE 1 Average HHI per country, by line of business (gross premiums). These figures show the average HHIs values, calculated on the database based on SNL data by year and by line of business (life/nonlife) as captured by gross premiums over the course of the available sample by country. For instance, the first bar from the left shows the average yearly HHI values of the life insurance industry in France in our data set. HHI, Herfindal–Hirschman Index. [Color figure can be viewed at wileyonlinelibrary.com]

La Motte (2014), as well as Baranoff (2015), insurance contracts in Japan offered generous guarantees on yields to policyholders, which ultimately turned detrimental to financial stability with the failure of many life insurance companies in the late 1990s and the early 2000s. This leads us to test the following hypothesis and investigate possible differences across countries:

Hypothesis 3 – *Bond portfolio investments offer protection to insurance companies, hence help reduce the risk of insolvency.*

Note that due to data constraints, we compare France and the United Kingdom with the United States in our analysis of the nonlife sector, and Japan to the United States in our analysis of the life sector. As a preview of our results, we show that it is possible to reject Hypothesis 1 most of the time. Indeed, ROA exhibits a stronger effect in the United States than that in France and Japan, but the difference is not statistically significant, except in the case of Japanese life insurance. Hypothesis 2 is verified for nonlife insurance in France, while Hypothesis 3 is verified in all countries, but a bit less significantly so in Japan.

4 | DATA

After explaining how the data were assembled to create a new international database on insurance impairments, we provide a few summary statistics.

4.1 | Constructing an international database of impairments

To build an international database on impairments, we extend to other countries of a similar level of financial development (France, Japan, and the UK) the approach followed in the insurance insolvency literature in the United States (especially on P/C insurance), which typically measures insolvency at the date of public intervention. Such a procedure ranges from action taken by courts, to intervention from the regulator as it triggers the suspension of new business, to the most severe case dimension being the liquidation of the insurance company.[4] BarNiv and McDonald (1992) on P/C insurance, for instance, define insolvency, including liquidation, receivership, conservatorship, restraining orders, and rehabilitation. The authors note that all mergers or acquisitions of insurers which cause the disappearance of the companies should not be regarded as distress or insolvency. Cummins et al. (1999) measure insurance insolvency in the nonlife industry by the first public regulatory order involving a company. Any formal state regulatory order including restrictions on management, conservation, rehabilitation, or liquidation was treated as a failure. These US failures were reported to the NAIC. Leverty and Grace (2012) define insolvent insurers as those affected by a formal regulatory action in the form of proceedings for conservation of assets, rehabilitation, receivership, or liquidation. Zhang and Nielson (2015) use A. M. Best's definition of insolvency: a company is financially impaired when the first official action is taken by the insurance department in its state of domicile, whereby the insurer can no longer conduct normal insurance operations.

[4]In many cases, the start of court proceedings allows the regulator to withdraw the license to underwrite business. For instance, in France, liquidation is possible either after the withdrawal of the license by the supervisor (liquidation is automatic for insurance companies but not for reinsurance companies), or in case of suspension of payments. For other types of procedures, the supervisor is informed and a mutual agreement is sometimes required.

State actions include supervision, rehabilitation, liquidation, receivership, conservatorship, cease-and-desist order, suspension, license revocation, administrative order, or any other action that restricts a company's freedom to conduct business normally. For Eling and Jia (2018), failure events include ceased operations, in liquidation or liquidated, in runoff, portfolio transfer, inactive, and insolvent insurance firms. However, Mergers & Acquisitions (M&As) were excluded.

The data for this study have been gathered from several sources, including guaranty fund associations,[5] the NAIC, the UK Prudential Regulation Authority (PRA), internal ACPR data, A. M. Best, and Bloomberg. The failure events or, as we term them, “impairments” are strictly defined as either a regulatory intervention of a local supervisor (leading to the suspension of the insurance license, which may only be temporary with a subsequent recovery) or the start of court proceeding in the form of rehabilitation or liquidation. With rare exceptions, these actions prevent firms in question from underwriting new business. The only jurisdiction in which firms could be allowed to underwrite new business following a supervisory intervention is the United States. Of the 1465 firms which entered receivership through 2016, only nine were recorded as being authorized to write or rewrite new business. Simple profit warnings or supervisory audits without actions limiting activity are not considered as impairments, nor are firms who enter run-off without knowing the motivation for this status. Lastly, M&As are excluded, as well as portfolio transfers, as we concentrate on cases where markets or supervisory authorities failed or did not intend to intervene ex ante.

Moreover, there are different ways to define an insurance company failure from an economic point of view. The scope of financial troubles leading to a failure could range from market warnings, substantial losses, partial suspension of activities, or withdrawal of agreement by the supervisor, with liquidation being the most extreme consequence. It is important to note that, as we have defined an impairment, some impaired firms in our database may eventually return to financial health, although in practice few do, and those who survive only do so thanks to a major restructuring or large-scale government bailout. We consider this definition helpful from a supervisory point of view, as it allows us to predict (and thus, hopefully, help prevent) any case that was destabilizing enough to prompt intervention, as opposed to just those cases which fit a specific legal definition (which may change across jurisdictions). Indeed, only considering liquidating firms would ignore cases of firms which were acquired following a supervisory intervention.

Following collection from the sources mentioned above purely regarding the impairments, our database contained 1607 cases across life and nonlife sectors. We include all major insolvencies described in Brennan et al. (2013) or Baranoff (2015) as well as many others. These company events are matched with available historical financial data for these companies. The latter data (principally, SNL data sets, described below) are also used to define a control sample of companies. Our study focuses on solo undertakings, excluding groups to the greatest extent possible. Such information was not always provided by our sources, requiring manual cross-checking. A main motivation to exclude groups was to isolate failing firms from a conglomerate, which can often fail either due to one unhealthy firm, or due to noninsurance-related financial troubles. We were therefore especially careful to exclude the parent company of any individual firm in our sample.

To be as comprehensive as possible, we used standard sources for historical financial data. This includes SNL Market Intelligence, the PRA (Bank of England) for UK cases, the Financial Services Agency for Japanese cases, and the French Prudential Supervision and Resolution Authority for

[5]Examples include the National Organization of Life and Health Insurance Guaranty Associations (NOLGHA), Property and Casualty Insurance Compensation Corporation (PACICC), Assuris, and Protektor.

French cases. We do not, however, have historical balance sheet and income statement data for all of the 1000+ identified cases of impairments. Taking the intersection of these impairments with the available series of historical financial data, we were left with 495 "impairments" out of 8893 total companies in our database. An additional data-treatment step consisted of determining the de facto date of failure for cases in which failure year provided by our sources surpassed the last available year of financial data. In such a limited number of cases, we associated the failure event with the last available firm-year data observation. We further note that the available data led us to concentrate on firms' risk management leading up to a failure, without addressing the issue of final dividend payouts to policyholders after, for example, a liquidation.

Finally, we cleaned the database of abnormal values, notably by dropping companies below $1 million in total assets and trimming values outside of the 1.5 and 98.5 percentiles, similar to Eling and Jia (2018) and Cummins et al. (1995), to correct for noise in our data which yielded economically implausible values in key ratios. The data set remains quite extensive with well over 50,000 (company-year) observations. Our final database contains 287 PC impairments and 150 life and health (LH) failures, totaling 437 across both, although we note that the number of impairment cases (i.e., impaired companies) included in most regressions (notably our baseline regression) is 263 (183 PC and 80 LH). This loss of cases in our estimates is due to a lack of correspondence between the available financial data of a firm in SNL and the year of its failure. To our knowledge, this figure remains the largest unique data set of its type for large countries in an academic study with a global perspective.

Macroeconomic data on 10-year government bond yields and the output gap were taken from the OECD Economic Outlook database. We adopt the output gap as a continuous measure of the macroeconomic cycle, while we use the long-term interest rate due to its linkages with the typical insurer's balance sheet.

4.2 | Summary statistics, impaired versus healthy

Below, we report a few summary statistics regarding companies which at some point become impaired, as compared with the control group of companies who remain healthy in our database.

As shown in Tables 1 and 2, financial ratios for impaired companies are on average quite different from those of healthy companies. Table 2 shows such t tests broken down by firm type

TABLE 1 Summary statistics with t test between impaired and healthy firms (all countries)

	(1) *Impaired*		(2) *Healthy*		(3) *Difference*	
	Mean	**SD**	**Mean**	**SD**	***b***	***t***
Avg T.A.	783,237	4,412,327	2,535,669	18,310,035	1,752,432***	(5.01)
Avg T.A. (the United States)	231,992	1,180,281	1,645,429	12,488,521	1,413,437***	(8.34)
Avg T.A. (Other)	6,009,040	12,906,406	43,880,341	83,438,740	37,871,301***	(5.15)
Observations	263		6974		7236	

Note: Full sample is an unbalanced panel which is comprised of 4382 observations for impaired firms, and 74,442 for our control sample of healthy firms. Numbers are represented in level after conversion to the USD for an even comparison.
***$p < 0.001$.

TABLE 2 Summary statistics of financial ratios with *t* tests between impaired and healthy firms, separated by sector

	(1) Impaired		(2) Healthy		(3) Difference	
Non life firms	**Mean**	**SD**	**Mean**	**SD**	***b***	***t***
ROA	−0.02	0.05	0.02	0.04	0.04***	(10.28)
ROE	−0.04	0.13	0.03	0.10	0.08***	(8.30)
ROA volatility	0.07	0.04	0.04	0.03	−0.03***	(−9.38)
ROE volatility	0.18	0.11	0.11	0.08	−0.08***	(−9.33)
Loss ratio	0.50	0.22	0.41	0.20	−0.09***	(−5.05)
Reinsurance ceded	0.34	0.20	0.32	0.24	−0.03	(−1.55)
Debt instruments	0.77	0.26	0.83	0.21	0.06**	(3.12)
Equity instruments	0.17	0.20	0.18	0.25	0.02	(0.98)
Real estate instruments	0.06	0.13	0.02	0.08	−0.04***	(−4.21)
Operating inefficiency	0.38	0.17	0.36	0.24	−0.02	(−1.26)
Observations	183		3358		3541	
	(1) Impaired		**(2) Healthy**		**(3) Difference**	
Life firms	**Mean**	**SD**	**Mean**	**SD**	***b***	***t***
ROA	−0.03	0.06	0.02	0.06	0.05***	(7.52)
ROE	−0.05	0.23	0.05	0.16	0.10***	(3.90)
ROA volatility	0.05	0.05	0.05	0.05	−0.00	(−0.45)
ROE volatility	0.21	0.11	0.15	0.12	−0.07***	(−4.88)
Reinsurance ceded	0.13	0.19	0.17	0.19	0.04	(1.32)
Debt instruments	0.75	0.28	0.86	0.24	0.11***	(3.46)
Equity instruments	0.17	0.24	0.15	0.26	−0.03	(−0.96)
Real estate instruments	0.09	0.18	0.04	0.14	−0.05*	(−2.43)
Operating inefficiency	0.34	0.32	0.36	0.46	0.02	(0.55)
Observations	80		3217		3297	

Abbreviations: ROA, return on assets; ROE, return on equity.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

(implying separate tables for nonlife and life insurers). Data on total assets have been converted into the USD in Table 1, while the data used for the ratios in Table 2 have been left in reported currency. A few striking conclusions can be drawn from these *t* tests.

First, Table 1 shows that failing companies generally tend to be smaller across all four countries, a stylized fact also shown in EIOPA (2018). We also confirm from our database the intuition that performance, as measured by ROA and ROE, is lower for firms which eventually fail. The latter group of companies exhibits more dispersion across all insurers in our study. Further, these

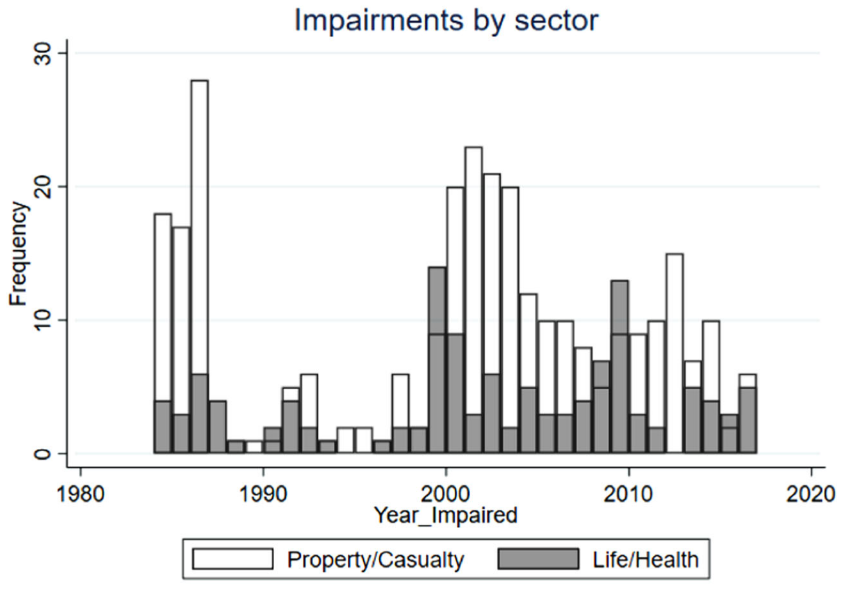

FIGURE 2 Histogram of life versus nonlife impairments. This figure shows the frequency of impairments by sector of activity. Life failures appear more correlated with financial cycles, with peaks around the bust of the dot-com bubble of 2000–2001 and the 2008 financial crisis.

performance measures are much less stable amongst firms that fail; indeed, the volatility of ROE is over twice as big for failing firms, even after trimming outliers as previously described.

Averaging over all periods, firms which fail appear to invest less in fixed-income investments, such as bonds, and slightly more in real estate. We also see that failing firms spend greater amounts in operating and administrative expenses, expressed as a share of written premiums. Further, while we have collected impairments as far back as 1975, the bulk of our balance sheet data for US firms begins in 1996 (our UK, Japanese, and French data begin in 1986, 1987, and 1992, respectively). We choose to only report in these histograms cases for which we have available financial data, and therefore which will be included (depending on the specification) in our regression results.

Figure 2 provides the evidence of the cyclical nature of impairments, with spikes in the United States in the mid-1980, in early 1990 associated with Hurricane Andrew, and in 2001 following the September 11 attacks (see Cheng & Weiss, 2012 for more on the role of hurricane exposure in the nonlife industry). Many studies, as mentioned above, also relate these waves with the increasing entry into the sector at the time. There are also spikes in impairments around the 2007 Financial Crisis for the US and non-US cases (as in EIOPA, 2018, for the latter, using a more restricted data set).

5 | EXPECTED RESULTS

As indicated above, "insurance ruin theory" explains why insurers fail when equity is too low, if assets face capital losses in case of a sudden increase in interest rates, or if reserves are not properly assessed, or operating costs are too high.

According to another approach, let us consider an insurer who holds a portfolio of N risks is introduced (see Plantin & Rochet, 2007). The insurer fails if $E + N(1 + \rho) \leq (\tilde{S}_1 + \tilde{S}_2 + \cdots + \tilde{S}_N)$, where ρ is the premiums collected on each of the N risks (they are assumed to be similar, without loss of generality, with mean normalized to one and standard deviation of σ). Using Chebyshev's inequality, this leads to:

$$Pr(default) \leq \frac{N\sigma^2}{(E + N\rho)^2}.$$

Defaults can therefore be avoided by increasing equity E, or N the number of risks, or tariffs ρ, or by decreasing σ through, for example, reinsurance. However, such a formula does not take into account the risks associated with an uncontrolled increase in the size of the portfolio. Furthermore, moral hazard or adverse selection needs to be taken into account, to ensure that shareholders and managers implement the appropriate internal risk control, or avoid management costs getting uncontrolled, and do not “gamble for resurrection” if they do not have enough “skin in the game,” or if their stakes decrease over time.

In our database, $Impairment_{jit}$ stands for an impairment of company j, in country i at time t. The determinants of impairments are individual financial indicators (balance sheet, P&L, etc.) as well as macroeconomic variables (interest rates, output gap, as indicated above). Regarding financial variables, we use ROA (net income/total assets), ROE (net income/total equity), total assets (in log), share of fixed-income investments in total investments, loss ratio (claims/gross Premiums), portion of gross premiums ceded to reinsurers, operating inefficiency (operating expenses/gross premiums), and the growth rate in gross written premiums.

The values used for the log of total assets (to control for size) have been converted to the USD. Since all other variables are ratios, values have been left in the reported currency. Note that we have chosen to use gross premiums so as to avoid a bias in the ratio (used to capture the size of the flow of business in a year) due to the choice of a firm to cede risks to a third party.[6]

Below, we map the expected sign for each parameter estimated in our baseline empirical analysis.

Variable	Impact on impairments	Hypotheses
ROA	(−)	Insurers running losses are more likely to become insolvent.
Size	(−)	Bigger firms (measured by the log of total assets) can better absorb shocks, and the law of large numbers should result in lower underwriting risk for larger firms.
Capital/reserves	(−)	Firms with higher risk-based capital have a low failure rate.
DebtIns	(−)	Fixed-income assets are often held to maturity by insurers, and are generally considered less risky.
LossRatio	(+)	Higher loss ratios erode PC insurers' bottom lines and own funds; higher values indicate lower financial health.

[6]Ambrose and Seward (1988) use (acquisition expenses + administrative expenses)/Gross premiums; Chen and Wong (2004) use a similar ratio.

Variable	Impact on impairments	Hypotheses
Reins	(−)	Depending on the reinsurance treaty, ceding premiums to a reinsurer can serve to transfer risk, lowering an insurer's exposure.
OpExp	(+)	Cost-inefficient firms mismanage their resources and perhaps engage in risky behavior to attempt to remain competitive.
PremGrowth	(−/+)	(+) For longer lags, fast-growing companies can lack underwriting prudence, and collect such volume precisely due to underpricing risks. An endangered firm may grow its business to gamble for resurrection. (−) On the other hand, in the short run, disreputable firms may struggle to collect premiums (e.g., following an A. M. Best downgrade), or may face surrenders, accelerating a failure.
IntRate	(−/+)	(−) Level has a negative effect on failures: higher interest rate levels provide higher returns for long-term bonds popular among insurers; (+) changes or upward movements may lead to disintermediation for certain life insurance contracts, as policyholders surrender to exploit higher interest rates available elsewhere.
OutputGap	(−)	To the extent that insurance risks (or the market risk borne in their investments) are correlated with recessions, macroeconomic crises pose a threat to insurers; in addition, personal financial distress associated with higher unemployment may lead policyholders to surrender.

Abbreviations: PC, property and casualty; ROA, return on assets.

6 | ECONOMETRIC APPROACHES

The empirical analysis is based on logistic regressions where we explain the likelihood of default events using a set of economic and financial determinants. We additionally estimate duration models in which the explanatory variables (depending on parametric definition) either help extend or serve to reduce a company's survival time in the sample. As logistic and duration models are very close, the second one may be viewed as a robustness check of the former; see Allison (1984) for a review of survival analysis.

6.1 | Fixed-effect logistic regression

In logistic regression, we assume the probability of impairment can be written as follows:

$$ln\left(\frac{p_{i,j,t}}{1-p_{i,j,t}}\right) = \beta_{i,t}\gamma_{i,t-k} + \delta_{i,t}\theta_{i,j,t-k} + \alpha_i + \alpha_t + \epsilon_{i,j,t-k}, \tag{1}$$

where the log-odds of becoming impaired at date t become a linear function of our explanatory variables (with $k \geq 1$).

$\gamma_{i,t}$ represents a vector of macroeconomic factors for country i, namely, the long-term interest rate and the OECD output gap. α_i is the country fixed-effect for country i, while α_t is the time fixed effect for year t. $\theta_{i,j,t}$ represents a vector of individual financial variables.

Further, we estimate predictive margins to evaluate our logit results in a more intuitive fashion. Instead of a covariate's effect on the log-odds, this transformation gives us:

$$\frac{\partial Pr(Impairment = 1 | X_1 = x)}{\partial X_1} = \frac{\Delta P}{\Delta X_1}$$

or, the effect on the predicted probability following a discrete change in an explanatory variable, X_1.

This can be done in a number of ways. The approach we adopt is to plot incremental jumps in a given variable (e.g., 2.5 pp jumps in ROA, from −10% to +10%), and calculate marginal effects using different "predictive margins" for each of these values. Computationally, this consists of calculating a predicted probability of failure ($\hat{p}$) for each observation after universally replacing ROA by the given value, while leaving the rest of the observed values for other variables unchanged.[7] By differencing these predictive margins obtained at two different given ROA values, we are able to understand the impact on the probability of failure due to a discrete change in this variable, keeping other variables at their observed values. For reference, we have additionally included such marginal effects where other covariates have been held at their *mean* values, which in practice does not severely impact our values.

6.2 | Survival analysis

To proceed with the parametric estimation of a survival model, we first assume survival time T to follow a certain distribution:

$$S(t) = P(T > t) = \int_t^{\infty} f(u)\,du.$$

The baseline distribution $f(t)$ in our estimations will be the Weibull distribution (although we test others as robustness checks):

$$f(t) = \lambda p t^{p-1} exp(-\lambda t^p).$$

This will yield, respectively, the following survival function:

$$S(t) = exp(-\lambda t^p)$$

and the hazard function $\left(h(t) = \frac{-dS(t)}{dt}\right)$ becomes in that particular case:

$$h(t) = \lambda p t^{p-1}.$$

[7]This is known as "average marginal effects." Values for $\hat{p}$ are then averaged across all observations, and a "predictive margin" for this ROA value is yielded.

If $p = 1$, the model becomes the exponential function with constant risk over time. $p > 1$ means risk increases over time, while it decreases through time with $p < 1$.

There exist two families of such so-called parametric survival models: proportional hazards (PHs) models and Accelerated Failure Time (AFT) models. In PH models, the covariates are assumed to have a multiplicative effect on the hazard function. PH regression thus estimates the effect of $exp(-x_j\beta)$ on the "hazard ratio," either accelerating or decelerating ($\lesseqgtr 1$) time to failure for each insurer:

$$\boldsymbol{h_i(t) = pt^{p-1}exp(\beta' x_j)} \tag{2}$$

where x_j is a vector of covariates, β is a vector of regression coefficients.

In the AFT framework, the dependent variable is the (log of) the survival time:

$$\boldsymbol{log\, t_j = x_j\beta + z_j}, \tag{3}$$

where z_j is the error term with a specified density. A one-unit increase in the covariates decelerates or accelerates the time to failure.

In our setup, we measure survival time as the number of 1-year periods a firm has survived relative to its origin—assumed to be the year in which its historical data series begins. At each period, a firm will either experience a failure (in which case its terminal survival time becomes known), or it will be considered "censored," meaning that the observation window ended before the individual experienced the event. This type of data is referred to as "right-censored." The likelihood function to be estimated for such data is written as follows:

$$L = \prod_{i=1}^{N} [f(T_i)]^{C_i} [S(T_i)]^{1-C_i}.$$

Noncensored observations thus contribute directly to the chosen density $f(T_i)$, while censored observations intervene in the survival function $S(T_i)$, contributing the information that a firm's terminal survival time T_i is at least later than the current measurement period t. In this way, all information from both impaired and never-impaired firms is taken into account in the estimation procedure.

For parametric estimations of PHs models, one typically reports hazard ratios instead of traditional coefficients; if the hazard ratio for a predictor is close to 1, then its effect is null. Hazard ratios are below one for variables which are "protective" or "healthy" (extend life), while values above are associated with increased risk. As with a logistic regression, all of the parameters are estimated taking the other predictors into account. Instead of hazard ratios, we here directly report traditional parameter estimates, which represent the increase in the expected relative hazard for each one-unit increase in the predictor, holding other predictors constant. Positive coefficients therefore are associated with shorter survival in the sample, and vice versa.

Note that in the AFT specifications, the interpretation of coefficients changes considerably, since the dependent variable is no longer the hazard rate but the survival time. With this approach, positive coefficients *delay* failure (as opposed to increasing the hazard rate under the PH metric), while negative ones accelerate failure. It should also be emphasized that such estimates can accelerate or decelerate time to failure without necessarily affecting the hazard rate, which can yield certain intuitive advantages to the approach depending on the specification.

7 | RESULTS

For our baseline logistic regression specifications, we include a single (interacted) country-year fixed effect, similar to Eling and Jia (2018), to account for the macroeconomic context and other jurisdiction-specific characteristics of a given country. Firm-level fixed effects could not be used for this type of analysis as it would drop the entirety of our control sample (i.e., those firms which never experience a failure since there is no variation to be explained in y_{it} (meaning $Pr(Default)$)). We later explicitly include macroeconomic variables (the output gap and the interest rate) as robustness checks, and further show specifications using separate time and country fixed-effects.

Our analysis is split across the two sectors owing to their innate differences: Tables 3 and 4 report our results for the nonlife sector, while Tables 5 and 6 report our life sector results. Separating the two sectors allows us to provide various contributions to the academic literature. We later discuss the ways in which these determinants vary across national jurisdictions.

7.1 | Nonlife sector

In this section, we will discuss our results that pertain only to the nonlife sector, found in Tables 3 and 4, before looking at cross-country differences (Table 7).

7.1.1 | Whole sample results

We first note that profitability, measured by ROA—used widely in the literature as a measure of firm performance—is strongly significant across all columns, as is ROE, for both approaches (logit or survival). At the margin, we find that a one standard deviation increase in ROA decreases the probability of default by 0.28 pp in absolute terms, or 0.23 pp when holding other covariates at their means. Zhang and Nielson (2015) also use ROE as a measure of profitability, similarly finding that higher levels help prevent failure, as the literature suggests for ROA. Higher loss ratios appear to weakly decrease survival (for a given level of ROA), implying that claims management and proper pricing help for the continuation of insurance firms. The significance of the loss ratio confirms the findings of Ambrose and Seward (1988) while again challenging Lee and Urrutia (1996) with a much more complete and current data set.

We also note that the coefficient for operating inefficiency is positive and significant across all specifications. This result confirms Zhang and Nielson (2015), who find a significantly higher expense ratio in a sample including 98 insolvent PC firms, and Leverty and Grace (2012) who show how managers can be responsible for running inefficient (and thus more failure-prone) firms. Our result remains novel given the breadth of our data and the choice of variable to instrument for operating inefficiency (*OpExp* variable in the tables). While our ratio (administrative and operating costs over premiums) is less complex than other techniques found in the literature (such as the Data Envelope Analysis approach in, e.g., Cummins et al., 2010), our approach is of increased practical interest to supervisors, who typically evaluate simple ratios to gauge the health of undertakings. Evaluated at the margin across all observed values, we find that a one standard deviation increase in our operating inefficiency measure (i.e., 23 pp) increases the probability of default by 0.15 pp. As shown in Figures 3 and 4, this absolute increase in $Pr(Default)$ should be understood as a deviation from the

TABLE 3 Logistic regression estimates (property–casualty sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA_{t-1}	−10.86***	−10.81***	−10.51***	−10.86***	−10.87***		
	(−9.37)	(−9.39)	(−9.28)	(−9.37)	(−9.42)		
ROE_{t-1}						−3.531***	−3.531***
						(−9.16)	(−9.16)
Size	−0.122*	−0.124*	−0.104*	−0.122*	−0.121*	−0.163**	−0.163**
	(−2.42)	(−2.51)	(−2.19)	(−2.42)	(−2.42)	(−3.13)	(−3.13)
$DebtIns_{t-1}$	−0.243	−0.344	−0.615	−0.243	−0.314	−0.373	−0.373
	(−0.72)	(−1.04)	(−1.94)	(−0.72)	(−0.94)	(−1.07)	(−1.07)
$LossRatio_{t-1}$	1.192**	1.153**	1.516***	1.192**	1.129**	0.897	0.897
	(2.73)	(2.67)	(3.63)	(2.73)	(2.61)	(1.93)	(1.93)
$Reins_{t-1}$	1.767***	1.744***	2.072***	1.767***	1.713***	1.790***	1.790***
	(3.83)	(3.84)	(4.65)	(3.83)	(3.76)	(3.77)	(3.77)
$OpExp_{t-1}$	1.286**	1.273**	1.387***	1.286**	1.267**	1.420**	1.420**
	(3.01)	(3.01)	(3.30)	(3.01)	(2.98)	(3.25)	(3.25)
$10YRIntRate_{t-1}$			0.518***	2.819	−0.147		3.558
			(6.88)	(0.33)	(−0.08)		(0.41)
$\Delta 10YRIntRate_{t-1}$			−0.0185	−1.132	0.0289		−1.473
			(−0.17)	(−0.37)	(0.03)		(−0.48)
$OutputGap_{t-1}$			−0.0207	2.173	−1.368		3.020
			(−0.50)	(0.18)	(−0.97)		(0.25)
Country-year fixed effect	Yes	No	No	Yes	No	Yes	Yes
Year fixed effect	No	Yes	No	No	Yes	No	No
Country fixed-effect	No	Yes	No	No	Yes	No	No
AIC	1726.6	1736.6	1771.2	1726.6	1739.8	1626.1	1626.1
Pseudo-R^2	0.146	0.142	0.122	0.146	0.144	0.137	0.137
Observations	28,801	28,930	32,059	28,801	28,930	28,685	28,685

Note: This table displays the results for different specifications of Equation (1), which models the probability of failure in the nonlife sector. The different columns vary in terms of explanatory variables and fixed effects as described in the bottom of this table. *t* statistics in parentheses.

Abbreviations: AIC, Akaike Information Criterion; ROA, return on assets; ROE, return on equity.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

unconditional firm-year probability of a default of 0.5 pp. Relative to this baseline probability, such a movement increases the probability of failure by 30%. When holding other covariates at their sample mean values, this amount drops slightly to 0.11 pp.

Looking at the asset side, we see that the share of bond instruments in a firm's investment portfolio, controlled by the other explanatory variables, is far outside of statistical significance

TABLE 4 Parametric survival analysis estimates with time-varying covariates (property–casualty sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA	−12.137***			−12.276***	8.663***	−12.093***	8.663***
	(1.112)			(1.096)	(1.215)	(1.087)	(1.093)
Size	−0.106	−0.162**	−0.176**	−0.092	0.076*	−0.106*	0.076*
	(0.054)	(0.059)	(0.058)	(0.053)	(0.038)	(0.050)	(0.036)
DebtIns	−0.646	−0.900*	−0.858*	−0.739*	0.503*	−0.702*	0.503*
	(0.340)	(0.378)	(0.373)	(0.333)	(0.248)	(0.339)	(0.248)
LossRatio	2.112***	2.100***	2.307***	2.182***	−1.561***	2.179***	−1.561***
	(0.383)	(0.449)	(0.427)	(0.374)	(0.310)	(0.350)	(0.279)
Reins	2.899***	2.990***	3.031***	2.881***	−2.085***	2.910***	−2.085***
	(0.422)	(0.472)	(0.458)	(0.418)	(0.362)	(0.375)	(0.335)
OpExp	1.498***	1.330*	1.178*	1.375***	−0.995**	1.389***	−0.995***
	(0.405)	(0.476)	(0.467)	(0.399)	(0.305)	(0.338)	(0.260)
OutputGap	0.062	0.072	−0.004	−0.017	0.007	−0.009	0.007
	(0.126)	(0.136)	(0.051)	(0.049)	(0.034)	(0.041)	(0.029)
IntRate	0.603***	0.650***	0.696***	0.430***	−0.457***	0.638***	−0.457***
	(0.149)	(0.158)	(0.110)	(0.090)	(0.063)	(0.098)	(0.055)
ROE		−4.047***	−3.967***				
		(0.368)	(0.355)				
Model	Cox PH	Cox PH	PH	PH	AFT	PH	AFT
Distribution			Weibull	Exponential	Weibull	Weibull	Weibull
Cluster	No	No	No	No	No	Firm	Firm
AIC	1558.1	1252.4	757.4	894.6	887.5	887.5	887.5
Observations	33,376	33,196	33,196	33,376	33,376	33,376	33,376

Note: This table displays the estimated coefficients of Equations (2) and (3), which model the probability of failures of nonlife insurers. The underlying probability distribution, estimated survival equation, and error clustering specifications are indicated at the bottom of this table.

Abbreviations: AFT, Accelerated Failure Time; AIC, Akaike Information Criterion; PH, proportional hazards; ROA, return on assets; ROE, return on equity.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

in the PC sector, directly challenging Lee and Urrutia (1996). Overall this result underscores the relative importance of the liability side of the balance sheet in this sector; due to the faster production cycle and shorter liability duration, a firm's efficiency (e.g., in settling claims) is of paramount importance for its survival. After splitting this sector off from the life sector, portfolio choice does not appear to play a significant role in predicting failure.

Perhaps unsurprisingly, after the inclusion of our country and time fixed effects, our macroeconomic variables lose all significance: the long-term interest rate is the only significant variable (see column 3 as compared with column 4). In our estimates, we find

TABLE 5 Logistic regression estimates (life sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA_{t-1}	−8.973**	−8.700**	−9.029***	−8.973**	−9.015**		
	(−3.28)	(−3.20)	(−3.81)	(−3.28)	(−3.29)		
ROE_{t-1}						−3.686***	−3.686***
						(−5.82)	(−5.82)
Size	−0.127	−0.130	−0.0229	−0.127	−0.126	−0.151	−0.151
	(−1.60)	(−1.64)	(−0.35)	(−1.60)	(−1.58)	(−1.80)	(−1.80)
$DebtIns_{t-1}$	−2.193***	−2.167***	−2.445***	−2.193***	−2.195***	−1.790**	−1.790**
	(−3.78)	(−3.79)	(−4.59)	(−3.78)	(−3.79)	(−2.83)	(−2.83)
$Reins_{t-1}$	−0.411	−0.000736	−0.252	−0.411	−0.356	−0.755	−0.755
	(−0.45)	(−0.00)	(−0.30)	(−0.45)	(−0.39)	(−0.73)	(−0.73)
$OpExp_{t-1}$	0.00687	0.0418	0.172	0.00687	0.0162	0.153	0.153
	(0.02)	(0.10)	(0.45)	(0.02)	(0.04)	(0.34)	(0.34)
$10YRIntRate_{t-1}$			−0.0428	−0.568	9.952		−1.038
			(−0.25)	(−0.56)	(0.92)		(−0.95)
$\Delta 10YRIntRate_{t-1}$			−0.134	0.282	−15.65		0.996
			(−0.56)	(0.32)	(−1.36)		(0.97)
$OutputGap_{t-1}$			0.0980	0.296	−0.0377		0.334
			(1.14)	(1.31)	(−0.07)		(1.46)
Country-year fixed effect	Yes	No	No	Yes	No	Yes	Yes
Year fixed effect	No	Yes	No	No	Yes	No	No
Country fixed-effect	No	Yes	No	No	Yes	No	No
AIC	437.4	448.9	492.9	437.4	447.4	378.6	378.6
Pseudo-R^2	0.158	0.159	0.073	0.158	0.175	0.201	0.201
Observations	6751	6892	10,215	6751	6892	6637	6637

Note: This table displays the results for different specifications of Equation (1), which models the probability of failure in the life sector. The different columns vary in terms of explanatory variables and fixed effects as described at the bottom of this table. t statistics in parentheses.

Abbreviations: AIC, Akaike Information Criterion; ROA, return on assets; ROE, return on equity.

$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

weak evidence of *higher* levels of ceded premiums to reinsurance being associated with a higher probability failure in the nonlife sector. This is in line with Leadbetter and Dibra (2008) which show reinsurance to be a contributing factor to insurance insolvency for 26% of the insolvencies in Canada during the 1960–2005 period. Two explanations are provided by the authors: complex intergroup arrangements, and overreliance on reinsurance assets that became more difficult to renew at some occasions. In our case, we interpret this as a self-selection effect, whereby less healthy insurers observe their risk levels, and attempt to share more of this risk with a third party. Our t tests confirm a

TABLE 6 Parametric survival estimates with time-varying covariates (life sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA	−13.870***		−14.035***		5.517***	−14.035***	5.517***
	(1.973)		(1.891)		(1.314)	(1.569)	(1.382)
Size	0.027	−0.001	0.034	0.009	−0.013	0.034	−0.013
	(0.063)	(0.081)	(0.063)	(0.081)	(0.025)	(0.059)	(0.025)
DebtIns	−2.577***	−3.245***	−2.466***	−3.291***	0.970***	−2.466***	0.970**
	(0.532)	(0.653)	(0.538)	(0.651)	(0.293)	(0.557)	(0.337)
Reins	−0.072	−0.496	−0.173	−0.402	0.068	−0.173	0.068
	(0.834)	(1.139)	(0.841)	(1.125)	(0.330)	(0.794)	(0.315)
OpExp	0.321	0.225	0.292	0.291	−0.115	0.292	−0.115
	(0.332)	(0.411)	(0.332)	(0.406)	(0.134)	(0.338)	(0.138)
IntRate	0.161	0.111	0.601**	−0.088	−0.236***	0.601*	−0.236***
	(0.307)	(0.501)	(0.232)	(0.185)	(0.063)	(0.253)	(0.063)
OutputGap	−0.140	−0.114	0.019	0.149	−0.007	0.019	−0.007
	(0.131)	(0.186)	(0.078)	(0.117)	(0.030)	(0.083)	(0.032)
ROE		−2.564***		−2.567***			
		(0.773)		(0.772)			
Model	Cox PH	Cox PH	PH	PH	AFT	PH	AFT
Distribution			Weibull	Exponential	Weibull	Weibull	Weibull
Cluster	No	No	No	No	No	Firm	Firm
AIC	422.5	264.5	280.5	200.3	280.5	280.5	280.5
Observations	11,814	11,541	11,814	11,541	11,814	11,814	11,814

Note: This table displays the estimated coefficients of Equations (2) and (3), which model the probability of failures of life insurers. The underlying probability distribution, estimated survival equation, and error clustering specifications are indicated at the bottom of this table.

Abbreviations: AFT, Accelerated Failure Time; AIC, Akaike Information Criterion; PH, proportional hazards; ROA, return on assets; ROE, return on equity.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

well-documented fact that reinsurance is more popular in the property–casualty sector than that in the life sector. Finally, we find that a lower loss ratio (claims/premiums) helps survival.

We also note that size matters for almost all our specifications, with a negative sign. This captures the fact that, ceteris paribus, smaller firms tend to have a less diversified portfolio of activities and are more likely to fail in comparison to larger undertakings.

Finally, our parametric survival model results are largely in line with our logit results: operating inefficiency significantly predicts failure, asset mix is not important and strong firm performance (ROA, ROE, and loss ratio) intuitively prevents insolvency.

TABLE 7 Cross-country logistic regression estimates (property–casualty sector)

	(1)	(2)	(3)
ROA_{t-1}	−10.51***	−10.55***	−10.83***
	(−9.28)	(−9.29)	(−9.61)
France × ROA_{t-1}		19.76	
		(0.55)	
UK × ROA_{t-1}		4.279	
		(0.23)	
Size	−0.104*	−0.104*	−0.119*
	(−2.19)	(−2.18)	(−2.44)
$DebtIns_{t-1}$	−0.615	−0.617	−0.424
	(−1.94)	(−1.94)	(−1.32)
$LossRatio_{t-1}$	1.516***	1.521***	1.296**
	(3.63)	(3.63)	(3.12)
$Reins_{t-1}$	2.072***	2.068***	1.882***
	(4.65)	(4.62)	(4.28)
$OpExp_{t-1}$	1.387***	1.377**	1.313**
	(3.30)	(3.27)	(3.10)
France × $OpExp_{t-1}$			6.368***
			(5.02)
UK × $OpExp_{t-1}$			2.134
			(1.53)
$10YRIntRate_{t-1}$	0.518***	0.522***	0.459***
	(6.88)	(6.87)	(6.23)
$\Delta 10YRIntRate_{t-1}$	−0.0185	−0.0199	−0.0305
	(−0.17)	(−0.18)	(−0.29)
$OutputGap_{t-1}$	−0.0207	−0.0212	−0.00465
	(−0.50)	(−0.51)	(−0.11)
Country-year fixed effect	No	No	No
Year fixed effect	No	No	No
country fixed-effect	No	No	No
AIC	1771.2	1774.7	1758.4
Pseudo-R^2	0.122	0.122	0.130
Observations	32,059	32,059	32,059

Note: This table compares life sector failure dynamics across European and US jurisdictions. *t* statistics in parentheses
Abbreviations: AIC, Akaike Information Criterion; ROA, return on assets.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

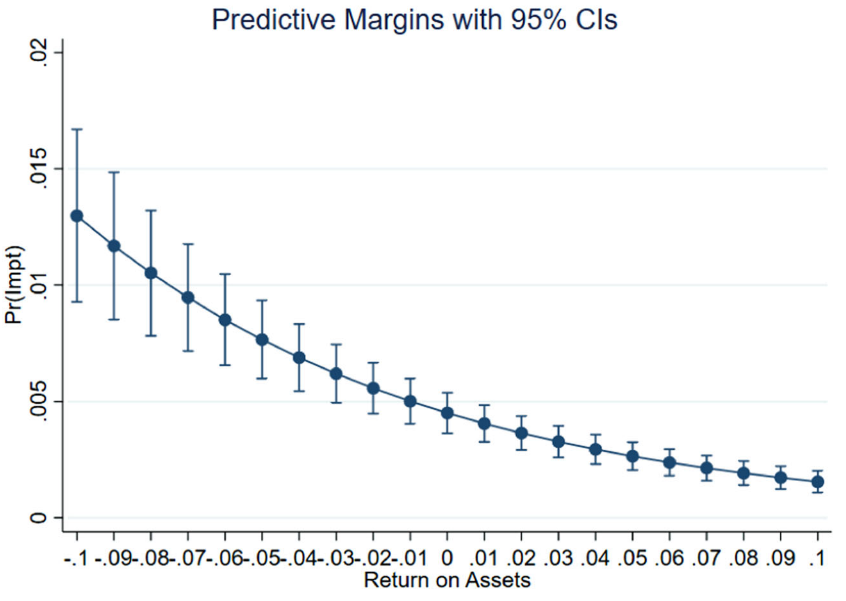

FIGURE 3 Predictive margins: ROA (nonlife). This figure shows the average predicted probability of failure, $\hat{p}$ for logit models, if all observations had the indicated ROA levels (while holding other covariates at their sample means). The dot is the mean probability on the *y*-axis for a given level of ROA on the *x*-axis. Two standard errors are provided above and below the mean estimate. We observe a clear negative relationship between ROA and $Pr(Default)$, although higher ROA values exhibit tighter confidence intervals (CIs) compared with lower ones. ROA, return on assets. [Color figure can be viewed at wileyonlinelibrary.com]

7.1.2 | Cross country: France and the UK versus the United States

As discussed above, differences across countries may be associated with supervisory activism that may pay more attention to certain specific indicators, or differences in market structure. In the second case, more competitive markets imply that any shock on costs is immediately passed on to policyholders via pricing, keeping margins constant. Conversely, in a market with monopoly power, firms do not adjust prices in response to shocks but instead reduce their margin—and as a consequence, such cost shocks may be more destabilizing.

As seen in Table 7, where we interact the ROA variable with country dummies (for France and the UK), the country interaction terms are not significant (implying no differential effect in France and the UK). However, for the same equation run on French insurers only, ROA becomes insignificant.[8] This is consistent with the positive sign of the coefficient of the dummy for France in Table 7 with a low t ratio (or a large standard deviation), hence offsetting the negative sign for ROA in the United States. In addition, repeating the same experiment for operating inefficiency, by adding country dummies interacted with that variable, we find a significant and positive coefficient for France (6.37), which should be added to the baseline effect on the log-odds (1.31). The coefficient is positive as well for the UK (2.13) but outside of statistical significance, so that no difference seems to exist for that variable for the UK. Overall, we can conclude that operating inefficiency matters most for

[8]Results are not reproduced here to save space but are available from the authors upon request.

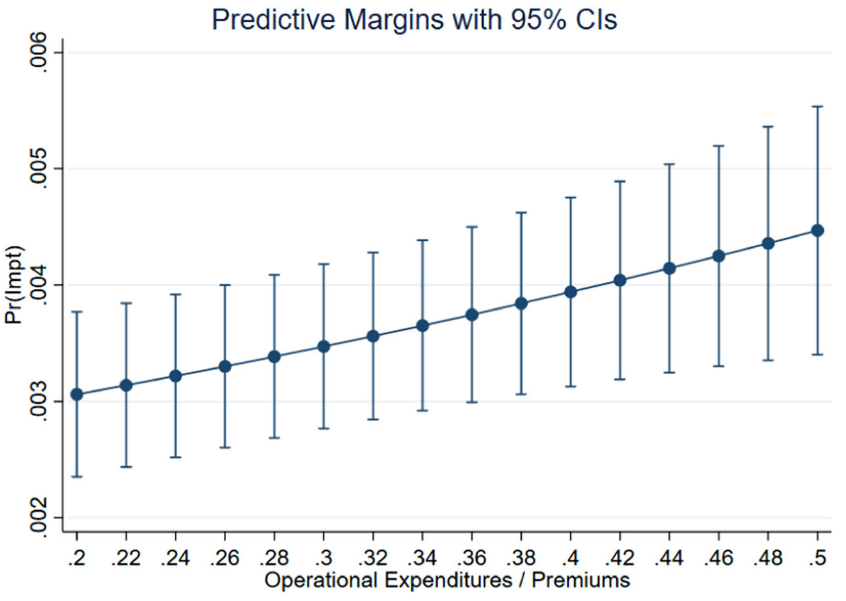

FIGURE 4 Predictive margins: Operating inefficiency (nonlife). This figure shows the average predicted probability of failure, $\hat{p}$ for logit models, if all observations had the indicated Operating Inefficiency levels (while holding other covariates at their sample means). The dot is the mean probability on the y-axis for a given level of Operating Inefficiency on the x-axis. Two standard errors are provided above and below the mean estimate. We observe a positive relationship between Operating Inefficiency and $Pr(Default)$, although with very large confidence intervals (CIs). [Color figure can be viewed at wileyonlinelibrary.com]

assessing insurance insolvency in the French case. These results are consistent with Figure 1: less competitive insurance markets with lower resistance to shocks appear to be more vulnerable. This confirms Hypothesis 2 in the case of France. When firms *do* fail in such jurisdictions, management problems can be laid bare, as suggested here by our results. Note, moreover, that this may also reveal more activist supervision as regulators intervene more strongly to shocks to operating costs.

7.2 | Life sector

7.2.1 | Whole sample results

As previously stated, by dividing the two sectors, we are able to emphasize their inherent differences. Our baseline life sector results can be found in Tables 5 and 6. In the life sector, we see that our firm profitability measures play a lesser role; ROA is more weakly significant in Tables 5 and 6. At the margin, a one standard deviation increase in ROA decreases the firm-year probability of default by 0.24 pp (0.18 with other covariates at their means, see Figure 5), compared with 0.28 pp in the nonlife sector. One explanation for this small contrast with the nonlife sector is the fact that profits and losses in the life insurance sector can be smoothed out

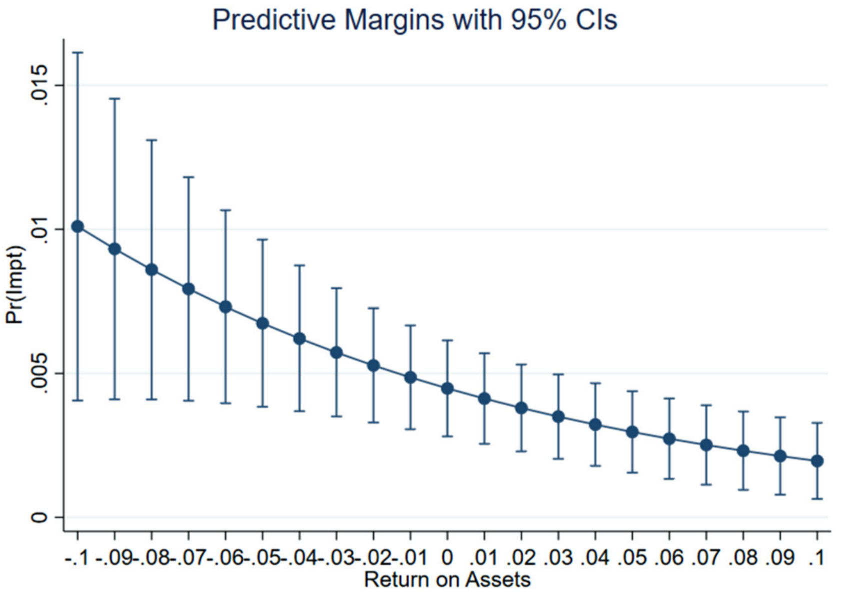

FIGURE 5 Predictive margins: ROA (life). This figure shows the average predicted probability of failure, $\hat{p}$ for logit models, if all observations had the indicated ROA levels (while holding other covariates at their sample means). The dot is the mean probability on the *y*-axis for a given level of ROA on the *x*-axis. Two standard errors are provided above and below the mean estimate. We observe a clear negative relationship between ROA and $Pr(Default)$, although higher ROA values exhibit tighter confidence intervals (CIs) compared with low ones. Confidence bands for this measure are universally higher in the life sector, demonstrating the importance of other variables. ROA, return on assets. [Color figure can be viewed at wileyonlinelibrary.com]

over several years,[9] implying less importance for the profitability of one given year. Nonlife firms, however, have no such smoothing mechanism helping them to remain competitive in bad times. The duration of the liability side is typically much lower in this sector, as well, regardless of jurisdiction. Lastly, reinsurance appears to play no role in firm survival for life companies.

The most striking difference from the nonlife sector is the importance of asset mix: the higher the share of bond instruments in total investments, the lower the probability of failure. This confirms our prior intuition that the asset side—and subsequent exposure to financial cycles—plays a larger role for life insurers. At the margin, a one standard deviation increase in the share of bond instruments in a life insurer's portfolio (i.e., 24 pp) decreases the probability of failure by approximately 0.23 pp (virtually unchanged when holding other covariates at the mean, see Figure 6). Operating inefficiency appears to play no role, in stark contrast to the results for the PC sector.

Overall, we broadly understand these differences to imply a heavier relative importance of market risk in the life industry, compared with the relatively larger factors of underwriting risk and efficient claims management in nonlife. This result confirms that life insurance—a sector with a longer liability-side duration—is ultimately more exposed to macroeconomic conditions, while providing a simple intuition that has not directly been addressed in the literature; Cheng

[9]In France, the *Provision pour participation aux bénéfices* allows insurers to distribute investment profits to policyholders up to 8 years after their realization.

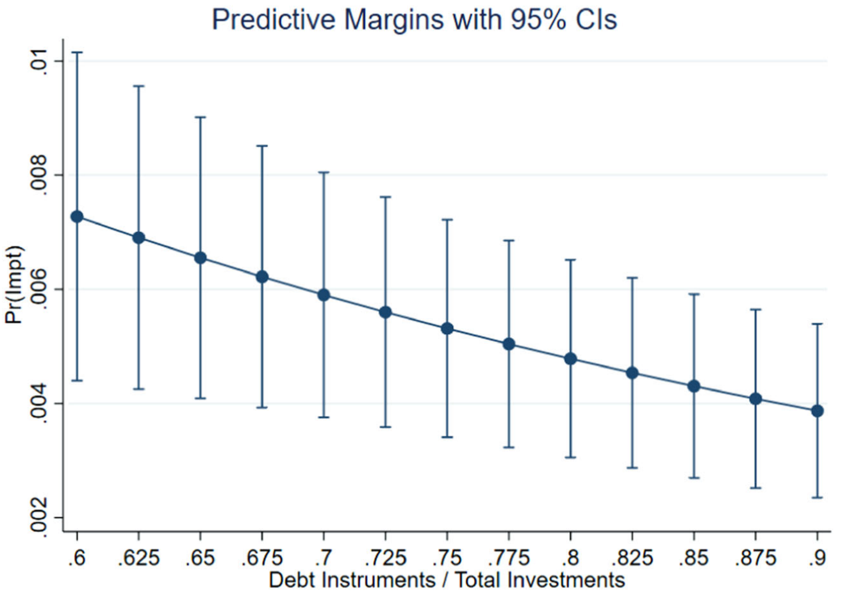

FIGURE 6 Predictive margins: Portfolio composition (life). This figure shows the average predicted probability of failure, $\hat{p}$ for logit models, if all observations had the indicated bond instrument share level (while holding other covariates at their sample means). The dot is the mean probability on the *y*-axis for a given level of Bond investment share on the *x*-axis. Two standard errors are provided above and below the mean estimate. We observe a clear negative relationship between the predominance of fixed-income instruments and $Pr(Default)$, although large confidence intervals (CIs) render it difficult to analyze at the margin. [Color figure can be viewed at wileyonlinelibrary.com]

and Weiss (2012) explore bond portfolio duration, but not fixed-income instruments as a portion of the total asset mix. This is also purely a study of nonlife insurers, and thus unable to highlight this marked difference regarding insolvency across these different business lines. Finally, as for the nonlife sector, most of our country-year fixed effects are significant (particularly in crisis years), reflecting the importance of country-specific macroeconomic conditions across all sectors.

As a means of model selection, we report the Akaike Information Criterion (AIC) as well as Receiver Operating Characteristic (ROC) curves. The ROC curves tell us, for a given level of sensitivity (or, rate of true positives) what rate of false positives (1-specificity) we must tolerate. For example, in the property–casualty logit with contemporaneous lags, a threshold of our indicator (the $\hat{p}$ of our estimation) which catches almost 90% of true insolvencies must come at the expense of a false alarm almost 25% of the time. While this underlines the difficulty of insolvency prediction, our Area Under the Curve (AUC) is in line with, although slightly higher than, the current literature (0.87, against 0.86 in Eling & Jia, 2018). This number nonetheless depends on the specification.

The AUC in ROC analysis serves as a measure of how good our estimated model is at discriminating between failures and nonfailures. An AUC of 0.5 represents a model which is no better than a random guess, while an AUC of 1 corresponds to a flawless predictor. Including both the cases of false positives and false negatives (Type I and Type II errors), an AUC of 0.87 corresponds to a model which yields an 87% chance of successfully distinguishing between impaired and nonimpaired firms.

TABLE 8 Cross-country logistic regression estimates (life sector)

	(1)	(2)	(3)
ROA_{t-1}	−8.910***	−9.268***	−8.271***
	(−3.76)	(−3.89)	(−3.43)
Japan × ROA_{t-1}		23.79	
		(0.65)	
Size	−0.0580	−0.0641	−0.117
	(−0.94)	(−1.02)	(−1.74)
$DebtIns_{t-1}$	−2.361***	−2.350***	−2.328***
	(−4.35)	(−4.25)	(−4.28)
Japan × $DebtIns_{t-1}$			1.992**
			(2.80)
$Reins_{t-1}$	−0.568	−0.553	−0.251
	(−0.64)	(−0.62)	(−0.28)
$OpExp_{t-1}$	0.194	0.205	0.164
	(0.50)	(0.53)	(0.41)
$10YRIntRate_{t-1}$	−0.0756	−0.101	0.00734
	(−0.45)	(−0.60)	(0.04)
$\Delta 10YRIntRate_{t-1}$	−0.0815	−0.0597	−0.130
	(−0.33)	(−0.25)	(−0.53)
$OutputGap_{t-1}$	0.0671	0.0635	0.0593
	(0.78)	(0.74)	(0.69)
Country-year fixed effect	No	No	No
Year fixed effect	No	No	No
Country fixed-effect	No	No	No
AIC	485.7	486.7	481.5
Pseudo-R^2	0.073	0.075	0.086
Observations	10,716	10,716	10,716

Note: This table compares nonlife failure dynamics across Japanese and US jurisdictions. t statistics in parentheses.
Abbreviations: AIC, Akaike Information Criterion; ROA, return on assets.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

7.2.2 | Cross country: Japan versus the United States

In this subsection, we compare the case of Japan (for which we have more exhaustive data for life insurance) to the US case. As seen in Table 8, for profitability, we notice that the coefficient on the interaction of ROA with Japan is nonsignificant. However, as in the case of nonlife insurance for France, the coefficient is positive with a low t ratio, offsetting the negative coefficient in the United States. This is consistent with the results of running the standard default prediction equation on Japanese life insurance companies only which leads to insignificant results for ROA, as well as for Total Assets (the size variable in the equation).[10] Life insurance in Japan therefore confirms Hypothesis 1. The results for Japan indicate that default is a more complex issue with ROA having a lower explanatory role. Insolvencies took also place in larger firms, so that the traditional negative relationship between size and defaults does not hold in Japan as it does in the United States. In addition, the effect of portfolio composition deteriorates in the Japanese jurisdiction, as evidenced by the statistically significant (positive) dummy variable interacted with the bond share variable, partly offsetting the positive overall coefficient. However, if the coefficient for Japanese firms on bond share is lower, it is not equal to zero. Indeed, an increase in bond share does reduce the likelihood of failure in Japan, but the elasticity is lower, as Japanese insurers exhibit more heterogeneity. Baranoff (2015) points to the role of high interest-bearing guarantees on life insurance contracts which were, in this case, linked to market rates. Bernard and La Motte (2014) also stress that, in the years preceding the wave of Japanese insurance failures, guarantees offered by these institutions were greater than those by government bond yields. As a consequence Hypothesis 3 is not fully verified in the Japanese case. Arguably, such a result should be investigated further, as it may also depend on the macroeconomic environment (in particular, the level of interest rates).

7.3 | Further analysis and robustness checks

We have included three additional tables as a means to both explore other dimensions and reaffirm the robustness of our previous results. We first include, in Tables 9 and 10, additional lags for our explanatory variables. While this serves as a robustness check, it also helps us understand the timeline of a failure and gives an idea of the predictive power of these ratios through time.

Indeed, in the nonlife sector, a profitability shock significantly increases the probability of failure as many as 3 years in advance, indicating a notable sensitivity to profitability shocks which may prove hard to correct. The coefficient for operating inefficiency only gains significance in the second year leading up to a failure, suggesting that managers can perceive and correct for inefficiencies before they prove fatal. In other words, a firm's profitability 3 years ago matters for their financial health, while misdeeds related to management have a more short-term impact.

A similar analysis is conducted in the life sector, which again exhibits a contrast with the nonlife sector. Here, ROA is only meaningful at the first lag; the second and third lags are firmly outside of statistical significance. The stronger leading indicator in this sector is the portfolio composition variable, which retains significance up to 3 years prior. We interpret this as a confirmation that profits and losses are more easily smoothed in the life insurance industry due to its longer liability duration, lessening the importance of past ROA shocks.

Indeed, these results also outline the long-term nature of life insurance; indeed, a life insurance firm, with a liability duration of 10 or more years, may survive a profitability shock so long as its investment income does not falter. Nonlife insurers, however, may struggle to recover from a bad surprise to the liability side, given the quicker speed at which they must settle their claims and the inability to smooth losses through time.

[10]Results are not reproduced here to save space but are available from the authors upon request.

TABLE 9 Additional lags (property–casualty sector)

	(T-3)	(T-2)	(T-1)	(T)
ROA	−8.395***	−10.17***	−10.81***	−13.09***
	(−5.65)	(−7.88)	(−9.39)	(−11.08)
DebtIns	−0.747*	−0.420	−0.344	−0.624
	(−2.08)	(−1.20)	(−1.04)	(−1.72)
OpExp	0.660	1.002*	1.273**	1.744***
	(1.21)	(2.13)	(3.01)	(4.01)
Country FE and year FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Pseudo-R^2	0.084	0.110	0.142	0.216
Observations	23,035	25,088	28,930	30,216

Note: *t* statistics in parentheses.

Abbreviations: FE, fixed effect; ROA, return on assets.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

TABLE 10 Additional lags (life sector)

	(T-3)	(T-2)	(T-1)	(T)
ROA	−1.362	−2.884	−8.156**	−14.90***
	(−0.35)	(−0.85)	(−3.03)	(−6.82)
DebtIns	−1.556*	−2.098***	−2.121***	−2.486***
	(−2.29)	(−3.45)	(−3.75)	(−4.35)
OpExp	0.394	0.613	0.114	0.374
	(0.91)	(1.68)	(0.28)	(1.00)
Country FE and year FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Pseudo-R^2	0.121	0.152	0.154	0.198
Observations	6045	7416	8046	8921

Note: *t* statistics in parentheses.

Abbreviations: FE, fixed effect; ROA, return on assets.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Next, in Table 11, we test various alternative specifications. Given the relatively strong presence of smaller firms in our database, we tested whether our results could be driven by these small, somewhat idiosyncratic players (e.g., mutual insurers) whose broader pertinence could be questioned. By excluding firms below \$10 and \$20 million thresholds (see columns 2 and 3 for nonlife insurance, and column 5 for life insurance), the previous results are unchanged, so that we can conclude that the results displayed in Tables 3–8 are robust to size. Further, given that we work mainly with ratios relative to levels of premiums, one may worry that our results are driven by a large drop or hike in the

TABLE 11 Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA_{t-1}	−8.477***	−7.839***	−8.053***	−8.428***	−6.228*	−6.228*	−5.093
	(−10.58)	(−5.46)	(−4.73)	(−4.63)	(−2.36)	(−2.36)	(−1.87)
$DebtIns_{t-1}$	−0.704**	−0.110	−0.435	−0.479	−1.868**	−1.868**	−1.968***
	(−3.22)	(−0.26)	(−0.92)	(−0.98)	(−3.24)	(−3.24)	(−3.30)
$OpExp_{t-1}$		1.819***	2.411***	2.111**	0.0568	0.0568	0.115
		(3.33)	(3.68)	(2.93)	(0.14)	(0.14)	(0.27)
$PremGrowth_{t-1}$				−0.139			−0.0929
				(−0.95)			(−0.45)
Country FE and year FE	Yes	Yes	Yes	Yes	Yes		Yes
Size	All	Above 10M	Above 20M	All	Above 10M	All	All
Sector	All	PC	PC	PC	LH	LH	LH
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.139	0.206	0.238	0.239	0.157	0.157	0.160
Observations	55,892	22,191	18,236	16,854	7807	7807	7711

Note: *t* statistics in parentheses.

Abbreviations: FE, fixed effect; LH, life and health; PC, property and casualty; ROA, return on assets.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

denominator of these ratios. By controlling for premium growth, our key ratios (operating inefficiency in nonlife, and bond investments in life) remain significant.

Finally, we carry out several additional checks in Table 12. In this table, we carry out the same analysis shown in Tables 3 and 5 but in the form of a single pooled regression. The interaction term in column (5) confirms our central life-sector result—that is, that portfolio composition matters for this sector but not nonlife—while our result with respect to operating inefficiency holds in column (6), albeit at the 10% significance level. ROA remains significant in the presence of these interaction dummies in the pooled regression. Further, we have created a distinct profitability variable that we introduce into several of each specification. As mentioned previously, most of the insurance default prediction literature evaluates the role of profitability (e.g., via ROA or ROE) as well as operating inefficiency. However, unprofitable firms may struggle to bring in premium revenue, which may lead to capturing the same financial fragility through two different variables (see notably Eling & Jia, 2018). We therefore orthogonalize ROA with respect to operating inefficiency, by simply regressing ROA on operating inefficiency and introducing the residual as a new (orthogonalized) ROA variable (displayed in tables below as *ROA**). When using this variable, we observe that the *OpExp* variable gains in significance and magnitude while other coefficients naturally remain unchanged. Additionally, we carried out this same analysis (ROA^*_{t-1} instead of ROA_{t-1}) for the regressions in Tables 7 and 8. This does not change the significance of our results.[11]

[11]These results are available upon request.

TABLE 12 Pooled regression

	(1)	(2)	(3)	(4)	(5)	(6)
Sector = Life	0.0420	0.0981	1.443**	1.443**	0.325	0.325
	(0.20)	(0.43)	(2.65)	(2.65)	(1.10)	(1.10)
ROA_{t-1}	−12.70*		−12.33*		−12.01*	
	(−13.07)		(−13.49)		(−13.03)	
$Life \times ROA_{t-1}$	3.438					
	(1.35)					
ROA^*_{t-1}		−12.69*		−12.33*		−12.01*
		(−13.01)		(−13.49)		(−13.03)
$Life \times ROA^*_{t-1}$		3.263				
		(1.28)				
$DebtIns_{t-1}$	−0.851**	−0.851**	−0.485	−0.485	−0.878**	−0.878**
	(−2.90)	(−2.90)	(−1.44)	(−1.44)	(−2.99)	(−2.99)
$Life \times DebtIns_{t-1}$			−1.886**	−1.886**		
			(−2.81)	(−2.81)		
$OpExp_{t-1}$	0.738**	0.856**	0.646***	0.786**	1.268**	1.404*
	(2.77)	(3.24)	(2.37)	(2.90)	(3.10)	(3.45)
$Life \times OpExp_{t-1}$					−0.953+	−0.953+
					(−1.68)	(−1.68)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macrovariables	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2141.5	2141.7	2136.3	2136.3	2140.5	2140.5
Pseudo-R^2	0.104	0.104	0.107	0.107	0.105	0.105
Observations	39,743	39,743	39,743	39,743	39,743	39,743

Note: t statistics in parentheses.

Abbreviations: AIC, Akaike Information Criterion; ROA, return on assets.

$^{+}p < 0.1$

$^{***}p < 0.05$; $^{**}p < 0.01$; $^{*}p < 0.001$.

8 | CONCLUSION

In this article, we present evidence of the intrinsic differences between the life and nonlife insurance sectors using a unique data set of so-called "impairments" manually assembled by the authors. Applying logistic regression and parametric survival analysis to a data set containing 150 life failures and 287 PC failures in four different countries, we show that the asset side plays a determinant role in predicting life failures, while the liability side (and the income statement) are the most important criteria for nonlife insurers. Asset mix (as captured by the part of fixed-income instruments in the total investment portfolio) significantly predicts failure for life insurers, while operating inefficiency (operating and administrative expenses over total written premiums) appears to play no role at all. The opposite is true in the nonlife sector: asset mix—highly significant in the life sector estimates—appears to play no role at all in nonlife, while operating inefficiency is significant across all specifications.

We understand this stark contrast to be a consequence of the differences in balance sheet structure between the two sectors. Life insurers can spread profits and losses out over the course of several years, in line with their longer liability structure. Depending on the branch of activity, nonlife insurers may have much shorter liability structures, meaning mismanagement (or, 1 or 2 bad years) may be enough to sink the firm given the ability of policyholders to lapse contracts more frequently. Nonlife insurers have no smoothing mechanism to remain profitable in bad years, leaving them vulnerable to profitability shocks, while life insurance contracts can often work like a savings instrument with less of a role for active or efficient claims management.

Importantly, beyond the results which confirm the literature on a more comprehensive database, we are able to draw conclusions regarding cross-country differences as the coefficients vary across not only sectors but national jurisdictions. Our results suggest that operating inefficiency also matters more in jurisdictions with more concentrated markets (e.g., France) with less incentive for efficient cost management. In the nonlife sector, we find that the protection afforded to insurers with a greater share of bond instruments can be mitigated in a jurisdictional context where unsustainable guarantees are offered to policyholders.

Regarding the policy and supervisory implications of our research, we provide evidence that insurance insolvencies do not come abruptly, as our indicators have some forward-looking properties. Insolvencies are predicted with a 3-year lag for ROA and 2-year lag for operating expenditure in P/C insurance. In the life sector, ROA predicts failure with a 1-year lag and the share of bond assets has predictive power with a 3-year lag. On the other hand, we do not find a confirmation that an acceleration of premium leads to difficulties a few years later. Macroeconomic variables play some role, confirming the literature, but it is not substantial and mainly concentrated on the level of interest rates. Here, such a variable is more a conditioning variable than one which highlights a transmission channel of vulnerabilities, as it may simply express the concentration of defaults at the beginning of our sample period.

All in all, a major contribution of this study is to uncover differences across countries, with a more significant effect of operating inefficiency (measured by operational expenditure ratio) in France characterized by a more concentrated market. In addition, while we also confirm the protecting role of bond investments for life insurance, this is less supported by the Japanese case, stressing the existence of other factors like the existence of guarantees on yield which play a big role in Japan during the 1990–2000 period.

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