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Analysing the determinants of insolvency risk for general insurance firms in the UK[☆]

Guglielmo Maria Caporale[a], Mario Cerrato[b], Xuan Zhang[c,*]

[a] Department of Economics and Finance, Brunel University London, Kingston Lane, Uxbridge UB8 3PH, United Kingdom
[b] University of Glasgow, United Kingdom
[c] Institute of Economics and Finance, Nanjing Audit University, China

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ABSTRACT

This paper estimates a reduced-form model to assess the insolvency risk of General Insurance (GI) firms in the UK. In comparison to earlier studies, it uses a much larger sample including 30 years of data for 515 firms, and also considers a much wider set of possible determinants of insolvency risk. The empirical results suggest that macroeconomic and firm-specific factors both play important roles. Other key findings are the following: insolvency risk varies across firms depending on their business lines; there is default clustering in the GI industry; different reinsurance levels also affect the insolvency risk of insurance firms. The implications of these findings for regulators of GI firms under the newly launched *Solvency II* are discussed.

1. Introduction

The UK's non-life insurance industry is worth £60bn and is the largest in Europe and the third largest in the world (after the US and Japan). It comprises more than 300 active firms (both domestically- and foreign-owned);[1] in addition, 94 Lloyd's syndicates also underwrite non-life business (Lloyd's Annual Report, 2014). In total, it currently generates approximately £48.217bn in gross written premium income (International Underwriting Association, 2015).

The failure of insurance firms may disrupt the financial industry as a whole, increase systemic risk and affect negatively the real economy. Solvency I (Directive 73/239/EEC) was introduced in 1973 for the prudential regulation of European insurance companies. It aimed to provide harmonised solvency requirements across the EU countries. It turned the EU into one of the most competitive markets in the world. Under Solvency I, all insurers in the EU applied one common solvency margin rule establishing the minimum capital requirements for insurance firms. However, Solvency I did not follow a risk-based approach and could not truly reflect the risk faced by insurers. For example, it considered the book value of assets instead of their market value.

Solvency II was launched on 1 January 2016, has been implemented in all 28 EU member states including the UK, and has achieved the harmonisation of asset and liabilities valuation techniques for insurance firms in the EU. In the UK it is managed by the Prudential Regulation Authority, Bank of England. Solvency II requires insurers to hold more capital, specifically to have 99.5% confidence to cover the worst expected losses over a one-year horizon. In this case the regulators are taking a risk-based approach to supervise firms: the riskier an insurer's business, the more provisions are required (which makes it important to investigate the probability of default of different business lines).

This paper analyses the determinants of insolvency risk for UK general insurance firms rather than non-life and life insurance firms; this is because the huge difference between non-life and life insurers makes it inappropriate to mix them together, as discussed in more detail in the next section. More specifically, it estimates forward-looking default probabilities that could be useful to the central bank to supervise local insurance firms (for example, it could take earlier action in the case of risky firms before they

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* Corresponding author at: Institute of Economics and Finance, Nanjing Audit University, 86 West Yushan Road, Nanjing 211815, China.

E-mail addresses: Guglielmo-Maria.Caporale@brunel.ac.uk (G.M. Caporale), xuanzhang.nanking@gmail.com (X. Zhang).

[1] In addition, more than 500 non-life insurance firms that are not regulated by the UK government are licensed by the European Economic Area to conduct business in the UK (Financial Services Authority, 2013).

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breach solvency capital requirements). The chosen model could be used to analyse such issues in other countries as well, with the empirical results helping policy-makers to improve regulations on the basis of country-specific features.

There exist very few studies providing evidence on default probabilities. This gap in the literature motivates the present paper. It is very difficult to access data on the insolvency risk of general insurance firms because very few have become "insolvent" – the majority choose instead to transfer their business to other insurance firms or just stop underwriting new business. As an alternative, third-party rating agencies may provide a good overview of their financial condition. The main problem with external rating agencies is that not all insurance firms are rated and the ratings normally stay the same for many years. Also, different rating agencies such as *A M Best, Standard & Poor's, Moody's* and *Fitch* have different rating methodologies and labelling systems.

Under Solvency II, insolvency risk is defined as the risk of loss (or of adverse change) in the financial situation of a company which results from fluctuations in the credit standing of issuers of securities, counterparties and any debtors to which a Solvency II undertaking is exposed, in the form of counterparty default risk, spread risk, or market risk concentration.[2]

In this paper, we assume that the insolvency risk of general insurance firms is made up of three components. The first is the credit quality of their investment portfolio, whose performance we measure using investment returns. The second is the counterparty risk through reinsurance activity and the purchasing of derivative contracts. A high reinsurance ratio and holding derivative contracts increase the credit risk exposure of firms. The reinsurance ratio and a dummy variable for the use of derivative contracts are therefore used in our study to capture this second component. In addition, the use of derivatives could also lead to an increase in the risk exposure of a firm, and thus its capital requirements and insolvency risk. The third is the direct default risk of insurers when their liabilities are greater than their assets and therefore they might become insolvent. The financial health of firms is measured here using the leverage, profitability, solvency and liquidity ratios. Size, growth and claims volatility are also taken into account.

We consider different exit situations for firms, including insolvency and transferring business to a third party. Ours is the first study to use a very large dataset consisting of 30 years of data for 515 firms to analyse the credit risk of general insurance firms in the UK. We show that other risk factors (macroeconomic and firm-specific factors), in addition to the standard ones considered by the literature (i.e. interest rates, liquidity, profitability and leverage) affect insurers' insolvency. When assessing their profitability, we take into account profit from both the traditional underwriting business and investment activities. We estimate both the individual probability of default (PD) for all available firms and the joint one using pair correlations. Ours is the first paper to analyse the systemic risk of general insurance firms in the UK on the basis of their individual PD. Our results show high dependence between general insurance firms when their individual PDs are high; this suggests that the joint probability of default is higher during distress times. Finally, we examine the relationship between reinsurance and change in the insolvency risk of general insurance firms. Previous studies find that primary insurers can benefit from reinsurance contracts in many ways (e.g. they can hedge against risk, and hold more capital to underwrite new business). We show that reinsurers may also benefit from reinsurance activities by reducing their credit risk.

The layout of the paper is as follows. Section 2 briefly reviews the relevant literature. Section 3 discusses the data and the various determinants of risk considered. Section 4 outlines the modelling approach. Section 5 discusses the empirical results. Section 6 summarises the main findings and offers some concluding remarks.

2. Literature review

Insurance firms play a very important role in the economy allowing individuals and firms to transfer risk for a premium. The bankruptcy of insurance firms may reduce financial stability. Many studies (Carmichael and Pomerleano, 2002; Das et al., 2003; Lee, 2013 and Lee and Chang, 2015) suggest that they can enhance financial stability by transferring risk to multiple parties through insurance and reinsurance activities. Rothstein (2011) shows that a healthy and well-developed insurance industry will improve the stability of financial markets. In addition, insurance firms protect individuals and corporations from losses arising from natural disasters such as floods etc. (Faure and Heine, 2011; Kugler and Ofoghi, 2005; Ward and Zurbruegg, 2000).

Only a few studies analyse the insolvency risk of insurance firms because the insurance industry is thought to be less exposed to turbulence in financial markets than other industries such as banking. There are several possible reasons for this difference. Unlike banks, insurers do not accept deposits from customers, and therefore they do not face the risk of a sudden shortage in liquidity that may cause bank runs. Harrington (2009) argues that insurance firms have to comply with more rigorous capital requirements than other financial institutions, and as a result credit events in the insurance industry have a small effect on the stability of the financial system as a whole. Das et al. (2003) suggest that the insurance industry is more stable because insurers do not suffer from bank runs, and the cancellation process for insurance policies takes longer than closing a bank account. Furthermore, because of larger premia, policy holders would suffer a loss if the policy were cancelled. Also, insurance firms often hold more long-term than short-term liabilities. Bell and Keller (2009) find that insurers are less interconnected than banks and there is less contagion among them. However, Janina and Gregor (2015) argue that insurance firms are becoming more similar to banks and increasingly contribute to the systemic risk of the financial sector. Further, a study by the Geneva Association (2010) indicates that the insurance industry increases systemic risk if insurers engage heavily in trading derivatives off the balance sheet or mismanage short-term financing activities.

Recent developments have made the insurance industry less stable; in particular, the fast growth of financial derivatives has meant that insurance firms have become more engaged with banks (through trading financial derivatives and other investment activities). Schinasi (2006) and Rule (2001) find that more insurance firms are buying credit default swaps to hedge their credit risk and using alternative risk transfer (ART) tools such as catastrophe bonds to transfer the catastrophe risk to other investors. Also, investment in asset-backed securities has increased. As a result, as pointed out by Baluch et al. (2011), insurance firms have become more vulnerable during crises. This is also shown by studies such as those by Das et al. (2003), who find that linkages through reinsurance activities may cause several primary insurance firms to fail at the same time, and by Acharya and Richardson (2014), who suggest that large insurance firms are more likely to invest in high-risk assets because they are correlated with different financial institutions. Given the fact that insurance firms are becoming riskier, it is crucial to examine the drivers of insolvency risk. One of the contributions of this paper is to assess the vulnerability of the UK insurance industry; to the best of our knowledge, this is the first time that this issue is examined in the case of the UK.

In addition, the close linkages between insurance firms and banking crises are such that the failure of the former greatly affects the stability of financial markets. For example, Main (1982) shows

[2] Art. 13(32) of the *Solvency II Directive*.

that banks can avoid some bad debts by working with them. This is because the information on obligors provided by insurance firms helps banks to understand better individual and corporate risk exposures. In addition, by mitigating the losses during natural disasters, insurance firms help to reduce the probability of default of some investors (policy holders, both individual and corporate) who, sometimes, are the same obligors as those of banks (Lee et al., 2016). Lehmann and Hofmann (2010) show that banks are more likely to transfer part or all of their risks to other financial sectors to avoid high correlation between assets that may lead to a higher default probability. Trichet (2005) shows that the insurance and banking industries are linked by ownership and the associations of credit exposure. As a result, insurance firms are playing a central role in financial markets and this may directly affect banks.

Analysing the insolvency risk of insurance companies and establishing what causes their bankruptcy can help central bank supervision and reduce systemic risks in the financial industry. Most previous studies on credit risk focus on banking crises; early warning systems are well developed for banks (e.g., Kaminsky and Reinhart, 1999; Borio and Drehmann, 2009; Drehmann and Juselius, 2014; Demirgüç-Kunt and Detragiache, 1998; Barell et al., 2010; Schularick and Taylor, 2012). A few papers also study general insurance firms in the UK. One of the most recent papers on the UK non-life insurance industry is by Adams and Jiang (2016), who examine the relation between outside board directors and six measures of financial performance using panel data for 1999–2012 drawn from the UK's general insurance industry. Analysing unbalanced (1987–2010) panel data, Upreti and Adam (2015) find that reinsurance enables primary insurers to have sufficient risk capacity for planning and pricing new business lines. Shiu (2011) uses data from 1985 to 2002 to investigate the relationship between reinsurance and capital structure; he shows that insurers with higher leverage tend to purchase more reinsurance, and those with higher reinsurance dependence tend to have a higher level of debt. Using the same database, Shiu (2007) shows that an insurer's size, liquidity, interest rate risk exposure, line of business concentration and organisational form are important factors associated with the decision to employ financial derivatives. Adam et al. (2003) explore the determinants of credit ratings in the UK insurance industry analysing a sample of 65 firms over the period from 1993 to 1997; they find that mutual insurers are generally given higher ratings than non-mutual ones, and also that liquidity and profitability have a significant positive effect on ratings.

Given the fact that insurance firms play a central role in financial markets and are becoming more engaged with banks, analysing their insolvency risk is clearly important. Within insurance firms, general insurers provide non-life insurance including property cover, health insurance, liability policies and miscellaneous financial loss cover for individual, firms and others. Unlike life insurers offering to individuals products such as annuities, conventional life insurance and other savings products, general insurance firms have shorter-term liabilities and are more vulnerable. Because of the big difference between general insurance and life insurance firms, it is inappropriate to mix them together. In the present study, we employ a reduced-form model to assess the insolvency risk for general insurance firms in the case of the UK.

3. Data and covariates

Firm-specific variables are collected from *SynThesys Non-Life.*[3] This consists of FSA (now regulated under the Prudential Regulation Authority, Bank of England) non-life annual return regulatory data. This database gives access to FSA return data for the current year and past years back to 1985. Over 400 companies are covered by the current *SynThesys Non-Life* system and the data include statements of solvency, components of capital resources, statements of net assets, calculations of capital requirement, analysis of admissible assets, liabilities, the profit and loss account, analysis of derivative contracts, summary of business carried on, technical account, analysis of premiums, analysis of claims, analysis of expenses, analysis of technical provisions etc. Also, approximately 180 ratios are included, with all the underlying calculations being done by *SynThesys*.

Since most general insurance firms are small and non-public, there is no specific default list. Further, in the UK market, instead of becoming insolvent, most general insurance firms go into 'Run-Off' (i.e. stop underwriting new business and wait for their financial condition to improve or transfer their business to others). All the credit events in our paper have been collected by hand from *Appendix D: Company Changes, Transfers, Mergers of SynThesys Non-Life UserGuide version 10.1,*[4] *PwC - Insurance insolvency*[5] *and Financial Services Compensation Scheme*,[6] and the final list[7] has been further discussed with technical specialists and senior supervisors from the Insurance Division at the Bank of England. Macroeconomic data have been obtained from the *World Bank*. Therefore, ours is a unique dataset for the insurance industry in the UK.

Before analysing the data, we remove firms without at least one-year balance data for all the variables. This is because such firms cannot be used to calibrate the model. We also remove firms for reasons such as merger and acquisitions or simply running off and disappearing. More discussion of the different types of firms' exit can be found in the model section. In the end, we are left with 366 firms with 14 firm-specific variables and 6 macroeconomic variables in our dataset spanning from 1986 to 2014. They include 35 firms that became insolvent during that period and 45 firms that exited owing to other reasons such as transferring their business to other firms.

To lessen the effect of outliers, we cap the reinsurance ratio and leverage ratio at the 95 percentile value and remove the lower 5 percentile value. We also cap the liquidity ratio, profitability ratio, combined ratio, growth premium written change, claim change and excess capital ratio at the 99 percentile value and remove the lower 1 percentile value. The summary statistics and correlation matrix of firm-specific and macroeconomic variables respectively are reported in Tables 1–3.

3.1. Covariates

Following the literature,[8] we choose the following firm-specific variables: leverage (Net Technical Provisions /Adjust Liquid Assets, *SynThesys* Appendix K: Ratio Definitions R12), profitability (underwriting profit to Total Assets), growth (the change in the natural logarithm of total admissible assets), firm size (the natural logarithm of total admitted assets), reinsurance (the ratio of Reinsurance Premiums Ceded to Gross Premium written), claims

[3] From *Standard & Poor'*.

[4] Updated on November 2014.

[5] http://www.pwc.co.uk/services/business-recovery/insights/insurance-insolvency-case-updates-pwc-uk.html.

[6] http://www.fscs.org.uk/what-we-cover/products/insurance/insurance-insolvencies/.

[7] The insolvency cases include AA Mutual Intl Ins, Andrew Weir Ins, Anglo American, Atlantic Mutual Intl, BAI (Run-Off), BlackSea&Baltic, Bryanston Ins, Chester St Emp, City Intl Ins, Drake Ins, Exchange Ins, FolksamIntl UK, Highlands Ins UK, HIH Cas&Gen Ins, Independent Ins, Island Cap Europe, London Auths Mut, Millburn Ins, Municipal General, North Atlantic Ins, OIC Run-Off, Paramount Ins, Scan RE, SovereignMar&Gen, UIC Ins, Baloise Ins Ukbr, East West Ins, Fuji Intl Ins, Hiscox Ins, Metropolitan RE, Moorgate Ins, Nippon InsCo Europe, Polygon Ins UK, Swiss RE (UK), Tower Ins Ukbr.

[8] Brotman (1989), Adams (1995), Pottier (1997, 1998), Adams et al. (2003) and Shiu (2011) etc.

Table 1
Summary statistics – full sample.
Maximum, minimum, median, average and standard deviation of firm-specific variables which including underwriting profit, leverage ratio, firm size, cash ratio, change of gross premium written, reinsurance ratio, change of incurred claims, growth ratio, change of excess capital, combined ratio, investment return and Herfindahl index of the whole industry.

	Max	Min	Median	Average	Std
PT	0.308	−0.296	−0.006	−0.007	0.064
Lev	4.692	−0.031	0.598	0.624	0.461
Size	17.834	1.289	11.315	11.341	2.180
CA	0.992	0.001	0.115	0.206	0.228
GPW %	11.208	−3.393	0.030	0.077	0.928
Rein	1.000	0.000	0.244	0.323	0.296
Claim %	25.891	−6.844	0.027	0.227	1.954
Growth	6.471	−9.448	0.009	0.017	0.413
Excess %	8.740	−4.156	0.049	0.168	0.959
Combined	326.000	0.032	0.481	5.436	25.757
InvR	0.110	−0.038	0.028	0.031	0.022
H-Index	1.000	0.000	0.763	0.714	0.280

Table 2
Summary statistics – default sample.
Maximum, minimum, median, average and standard deviation of firm-specific variables which including underwriting profit, leverage ratio, firm size, cash ratio, change of gross premium written, reinsurance ratio, change of incurred claims, growth ratio, change of excess capital, combined ratio, investment return and Herfindahl index of default firms.

	Max	Min	Median	Average	Std
PT	0.288	−0.241	−0.018	−0.025	0.058
Lev	4.626	−0.001	0.806	0.865	0.594
Size	15.251	5.816	11.458	11.327	1.661
CA	0.969	0.001	0.120	0.194	0.197
GPW %	8.026	−3.393	−0.067	−0.098	0.946
Rein	1.000	0.000	0.442	0.445	0.266
Claim %	25.073	−6.044	0.009	0.089	1.763
Growth	1.590	−1.417	−0.020	−0.009	0.285
Excess %	6.971	−3.427	0.007	0.085	1.012
Combined	285.200	0.037	0.554	8.142	29.902
InvR	0.087	−0.034	0.020	0.023	0.019
H-Index	1.000	0.185	0.785	0.731	0.260

change (the change in net claims incurred), capital (the change in excess capital resources to cover general business CRR), liquidity (Cash/Total Asset: the ratio of the sum of cash and short-term investments to total assets), gross premium written (the annual change in gross premium written), combined ratio (Incurred Claims + Management Expense) / Gross Premium Written), Line-of-Business Concentration (Herfindahl index), organisational form (mutual or non-mutual firm) and a derivative dummy variable (defined on the basis of *SynThesys* form 17,[9] i.e. whether the sum of form 17 is zero or not). In addition, we also include UK macroeconomic variables, namely GDP growth, the change in the wholesale price index (2010 = 100), the change in foreign direct investment, net inflows, the real interest rate, the real effective exchange rate index (2010 = 100) and the change in the credit provided by financial institutions (% of GDP), all series coming from *the World Bank*.

[9] Our dataset does not allow to distinguish between exchange-traded and OTC derivatives. Using the information from form 17, it includes the following types of derivatives used: Fixed-interest securities; Futures & contracts for differences: Interest rates; Futures & contracts for differences: Inflation; Futures & contracts for differences: Credit index/basket; Futures & contracts for differences: Credit single name; Futures & contracts for differences: Equity Index; Futures & contracts for differences: Equity Stock; Futures & contracts for differences: Land; Futures & contracts for differences: Currencies; Futures & contracts for differences: Mortality; Futures & contracts for differences: Other; options: Swaptions; options: Equity index calls;options: Equity stock calls; options: Equity index puts; options: Equity stock puts; options: Options.

3.1.1. Traditional risk factors

Traditional risk factors such as leverage, profitability, firm's growth rate, firm size, and liquidity are also important for assessing the insolvency risk of insurance firms. First, higher leverage may have an adverse effect on them by affecting their underwriting performance and making an insurer's capital more vulnerable to economic shocks. Further, Adams et al. (2003) find that insurers with lower financial leverage are more likely to be given a higher credit rating. Previous studies such as Brotman (1989) and Pottier (1997, 1998) also report a negative relationship between financial leverage and the capital structure of insurance firms. Second, profitability (in our case, we split it into underwriting profitability and investment return) indicates the ability of insurance firms to generate a surplus to develop their current business and generate new business. A higher profitability ratio means that an insurance firm can manage expenses effectively and set competitive premium rates. Titman and Wessels (1988) and Frank and Goyal (2009) suggest that highly profitable firms have a lower debt ratio and hence a lower credit risk. Third, normally a positive firm's growth rate signals a good financial condition of that firm, but for issuers with significant new business growth could be achieved by poor underwriting standards and mispricing strategy (Adams et al., 2003). Borde et al. (1994) and Pottier (1997) find that this will lead to greater uncertainty about the capital reserve risk for insurance firms. Further, Frank and Goyal (2009) conclude that firms with a high growth ratio face more debt-related agency issues and higher associated cost. Fourth, studies such as Bouzouita and Young (1998) find that large insurers are less likely to become insolvent; they normally benefit from economies of scale, and given their sizeable market shares and higher ratings have lower financing costs than small insurers (Adams et al., 2003). Fifth, we use the cash ratio as a measure of a firm's liquidity. For insurance firms, a high liquidity ratio indicates good claim-paying ability. Previous studies such as Carson and Scott (1997) and Bouzouita and Young (1998) show a negative correlation between the liquidity risk and the credit rating of insurance firms.

In addition, some commonly used macroeconomic variables such as GDP growth,[10] Wholesale Price,[11] Foreign Direct Investment,[12] Real Interest Rate,[13] Real Effective Exchange Rate,[14] Credit provided by Financial Institutions[15] are also included in our model.

[10] The annual percentage growth rate of GDP at market prices is calculated using values in 2005 US dollars.

[11] Change of Wholesale Price Index (2010=100). The wholesale price index includes a mix of agricultural and industrial goods at various stages of production and distribution, including import duties.

[12] Change of Foreign Direct Investment, Net Inflows. Foreign Direct Investment is defined as direct investment equity flows in the reporting economy. It is the sum of equity capital, reinvestment of earnings, and other capital. Direct investment is a category of cross-border investment associated with a resident in one economy having control or a significant degree of influence on the management of an enterprise that is resident in another economy.

[13] The real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator. The terms and conditions attached to lending rates differ by country, however, which limits their comparability.

[14] Real Effective Exchange Rate Index (2010=100). The real effective exchange rate is the nominal effective exchange rate (which measures the value of a currency against a weighted average of several foreign currencies) divided by a price deflator or cost indexs.

[15] Change of Credit provided by Financial Institutions (% of GDP). Domestic credit provided by the financial sector includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net. The financial sector includes monetary authorities and deposit money banks, as well as other financial corporations when data are available (including corporations that do not accept transferable deposits but incur such liabilities as time and savings deposits). Examples of other financial corporations are finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange companies.

Table 3
Correlation matrix of firm-specific variables.
Correlation matrix of underwriting profit, leverage ratio, firm size, cash ratio, change of gross premium written, reinsurance ratio, change of incurred claims, growth ratio, change of excess capital, combined ratio, investment return and Herfindahl index of the GI firms.

	PT	Lev	Size	CA	GPW %	Rein	Claim %	Growth	Excess %	Combined	InvR	H-Index
PT	1.000	−0.271	−0.078	0.084	−0.002	−0.074	−0.074	−0.008	0.094	−0.023	−0.098	0.129
Lev	−0.271	1.000	0.352	−0.203	−0.006	−0.081	0.022	0.012	−0.040	0.018	−0.052	−0.173
Size	−0.078	0.352	1.000	−0.417	−0.012	0.003	0.003	0.152	0.053	−0.074	−0.081	−0.456
CA	0.084	−0.203	−0.417	1.000	0.054	−0.163	0.013	0.014	0.028	−0.006	0.161	0.178
GPW %	−0.002	−0.006	−0.012	0.054	1.000	−0.047	0.226	0.318	0.020	−0.092	0.005	−0.055
Rein	−0.074	−0.081	0.003	−0.163	−0.047	1.000	0.000	−0.039	−0.001	0.040	−0.325	−0.137
Claim %	−0.074	0.022	0.003	0.013	0.226	0.000	1.000	0.185	0.015	0.000	0.009	−0.003
Growth	−0.008	0.012	0.152	0.014	0.318	−0.039	0.185	1.000	0.253	−0.128	−0.046	−0.070
Excess %	0.094	−0.040	0.053	0.028	0.020	−0.001	0.015	0.253	1.000	−0.019	−0.004	−0.005
Combined	−0.023	0.018	−0.074	−0.006	−0.092	0.040	0.000	−0.128	−0.019	1.000	−0.047	0.120
InvR	−0.098	−0.052	−0.081	0.161	0.005	−0.325	0.009	−0.046	−0.004	−0.047	1.000	−0.057
H-Index	0.129	−0.173	−0.456	0.178	−0.055	−0.137	−0.003	−0.070	−0.005	0.120	−0.057	1.000

3.1.2. Insurance-specific risk factors

We also include insurance-specific factors such as reinsurance, incurred claims growth, capital, gross premium written growth, a derivative dummy, organisational form, combined ratio, and line-of-business concentration to capture the additional default risk information within the insurance industry.

First, reinsurance is widely used by insurance firms to reduce capital requirements but makes them exposed to counterparty risk. Berger et al. (1992) point out that there are two types of traditional reinsurance activities involving a direct insurer ceding all or part of its assumed underwritings to another insurance company. Insurance firms transfer part of their risk to third parties by reinsurance, which results in lower uncertainty concerning their future losses and enables them to reduce their capital reserves. Adams (1996) suggests that reinsurance improves the ability of the primary insurer to survive an external economic shock. On the other hand, the financial health of a heavily reinsured firm will be adversely affected by the insolvency of reinsurance firms. It should be noticed that the reinsurance firms discussed in Section 5 are those taking reinsurance from primary insurers.

Second, claims' growth[16] will directly affect the capital of an insurance firm. In the insurance industry, incurred claims are the amount of outstanding liabilities for policies over a given valuation period. A significant increase in net claims may generate liquidity risk for an insurer, which will eventually become insolvent if it cannot raise enough capital.

Third, the capital used to cover the insurance business is a key factor. When measuring the default risk of insurance firms, it is natural to include the Excess (deficiency) of capital resources to cover general business CRR (Capital Requirements Regulation). Insurance firms should hold enough capital to cover the policies they underwrite.

Fourth, the growth in the gross premium written reflects how well an insurance firm is running its core business; a rapidly growing gross premium written may indicate potential huge losses (claims) in the future. Generally speaking, an increase in gross premia written[17] indicates that the insurance firm is in a good financial condition. Incorporating this variable into the model will automatically exclude 'run-off' firms from the sample; these are very common in the insurance industry (insurance firms can stop underwriting business but still exist for many years).

Fifth, whether or not an insurance firm is involved in derivative trading will affect its credit risk; hence, we add a derivative dummy to our model. Shiu (2011) notes that insurers use derivatives to hedge risk, which may also increase their exposure to counterparty risk (for OTCs). The dataset does not allow to distinguish between OTC and exchange trade derivatives, but it does differentiate between derivatives for investment and hedging. Our data[18] are consistent with the findings of Shiu (2011), who reported that most insurers use derivatives for hedging purposes, and therefore their insolvency could increase because of these hedging activities (i.e. counterparty risk from OTCs or market risk from imperfect hedging). Following his study, we obtain label 1 for a derivative user by looking for nonzero values from Form 17 of the PRA returns. For example, if insurance firms trade derivatives (in which case they report the derivatives usage in form 17, and therefore the sum of form 17 will not be zero) then the dummy takes value 1, otherwise it is set equal to 0.

Sixth, since most general insurance firms are not publicly listed, firms with different organisational forms, including mutual and non-mutual, can behave differently. Adams (1995) argued that the organisational form can partly affect the decision-making of insurance firms. A mutual insurance firm is an organisation that supplies insurance services, and that is owned by its customers, or members, which means that there are no shareholders to pay dividends to or to be accountable to. Such a firm can concentrate entirely on delivering products and services that best meet the needs of its customers. In our analysis we separate mutual and non-mutual firms.

Seventh, insurance firms writing more new business (i.e. with fast growth in gross premium written) are normally in good financial health, but there is a potential mispricing problem (firms use a cheap premium to increase sales but do not generate enough money to cover future claims). This is captured by the combined ratio in our model, which is defined as Incurred Claims + Management Expense) / Gross Premium Written to capture any mispricing by insurers.

Lastly, insurance firms usually run business in different areas; if the business is highly concentrated in a single area, this may lead to huge losses. For example, an insurance firm focusing on properties will suffer a lot when floods or earthquakes happen. As a result, insurers with a high line-of-business concentration may have a higher earning risk. We follow Shiu (2011) in using the Herfindahl index H at the firm level to proxy the line-of-business concentration (a higher number indicates a lower level of business mix,

[16] The difference in annual incurred claims.

[17] These are the total premia written, which include both direct and assumed premia written, before any reinsurance.

[18] We checked the data on derivatives for hedging and investment and noticed that only 8 data-points correspond to trading derivatives for investment (i.e. insurance firms receive a fixed payment in exchange for taking risk). As a robustness test, we report the regression results in Appendix C when removing the 8 data-points for investment; the results are consistent with our original results.

the max value is 1), which is defined as:

$$H = \sum_{i=1}^{N} S_i^2 \tag{1}$$

where s_i is the premium written for business line i as a percentage of the Gross Premium Written (i.e. divided by the total premium written for all business lines), and N represents the number of different types of business lines in which the firms are involved.

3.2. Summary statistics

As already pointed out, the insurance industry is relatively more stable than other industries. This is confirmed by Table 1, which shows that the standard deviation (Std) of underwriting profitability (PT) and investment return (InvR) is very small.[19]

Insurance firms, on average, have a higher investment profit than the traditional underwriting profit.[20] This could be driven by derivative trading (Schinasi, 2006; Rule, 2001). On average, general insurance firms in the UK have high capitalisation, the reason being that they have to comply with more rigorous capital requirements than financial institutions (Harrington, 2009). The size of firms changes a lot over the sample period that we are considering, suggesting that, although the industry as a whole is relatively stable, many insurance firms transfer their business to others before they become insolvent.[21] This is also why we consider the transfer of business to other companies as a possible form of exit. The high volatility of the combined ratio (Combined) could be due to mispricing problems. The Herfindahl index is 0.714 on average, with a small standard deviation. This further supports the view that insurance firms are stable and their business is not very diverse.

Table 2 shows that, over the full sample, on average default firms have a negative underwriting profit (PT) and change in gross premium written (GPW %), a low cash ratio (CA), a small incurred claim increase (Claim %), a small excess capital increase (Excess %) and a low investment return (InvR). This may indicate that they lose money from their main business and their investment performance is not as good as in the case of other firms. They are relatively small-size firms with slow business growth, and holding less capital makes them more vulnerable. They also have higher leverage, reinsurance ratio, combined ratio and Herfindahl index (H-index), which suggests that they are more exposed to interest risk, credit risk and market risk. Overall, the evidence in Table 2 confirms the previous findings of the literature (see, e.g., Adams et al., 2003 and Shiu, 2011).

Table 3 shows the correlation matrix of the 12 firm-specific variables. No evidence of high correlations is found for any firm-specific variables; the maximum correlation is below 0.5. Underwriting profitability (PT) is negatively correlated to leverage (Lev) and the reinsurance ratio with a value of −0.271. This suggests that financing activities through debt and reinsurance may reduce profits. Another interesting finding is the negative correlation between PT and investment return; this supports our variable analysis in the previous section that splits profitability into core business (underwriting business) and investment activities.

Firm size has a positive relationship with leverage (Lev) but a negative one with the cash ratio (CA), which indicates that large firms are relatively more leveraged and hold less cash.

Gross premium written has a positive relationship with both firm's growth (0.318) and claims change (0.226). This suggests that if insurers write more premiums this will lead to a fast growth of the firm, but one should also take into account the potential cash outflows from large potential claims in future. It is important therefore for the model to capture mispricing problems by incorporating the combined ratio that is typical of firms growing rapidly and writing more business.

Finally, firm size and the Herfindahl index (H-index) are negatively correlated with a value of −0.456, which suggests that large firms have a relatively less concentrated business.

4. The model

Default risk modelling has developed considerably in recent years. Beaver (1966, 1968) and Altman (1968) first proposed credit scoring models that calculate the default probability for a firm using accounting-based variables. The structural model, first used by Merton (1974), applies option theory to derive the value of a firm's liabilities in the event of default.

There are several issues arising in the context of such models. Estimating the probability of default on the basis of accounting data amounts to trying to predict a future event using financial statements designed to capture the past performance of a firm; therefore, the obtained estimates might not have strong predictive power about the future status of the firm. Also, Hillegeist et al. (2004) find that, owing to the conservatism principle, fixed assets and intangibles are sometimes undervalued relative to their market prices causing accounting-based leverage measures to be overstated. As for the structural model, the value of a firm's assets is estimated at market prices; however, these may not contain all publicly available default-related information on the firm. Also, the term structure, off-balance and other liabilities are not well specified in structural models when calculating the default threshold of the firm, which may lead to inaccurate estimates of the default probability.

For these reasons, in this paper instead we estimate default probabilities using reduced-form models that have become increasingly popular for individual firms in recent years. Jarrow and Turnbull (1995) first introduced this type of models, which were then extended by Duffie and Singleton (1999). They assume that exogenous Poisson random variables drive the default probability of a firm. A firm will default when the exogenous variables shift from their normal levels. The stochastic process in the model is not directly linked to the firm's assets value. This makes the models more tractable. Duffie et al. (2007) first proposed a doubly stochastic Poisson model with time-varying covariates and then forecast the evolution of covariate processes using Gaussian panel vector autoregressions. The model was further developed by Duan et al. (2012), who applied a pseudo-likelihood method to derive the forward intensity rate of the doubly stochastic Poisson processes at different time horizons.

The Poisson process with stochastic intensities has been widely applied to model default events. The specification adopted in this paper assumes that the stochastic intensity has a linear relationship with macroeconomic and firm-specific variables. A doubly-stochastic formulation of the point process for default is proposed by Duffie et al. (2007), with the conditional probability of default within τ years being given by

$$q(X_t, \tau) = E\left(\int_t^{t+\tau} e^{-\int_t^z (\lambda(u)+\varphi(u))du} \lambda(z)dz | X_t \right) \tag{2}$$

where X_t is the Markov state vector of firm-specific and macroeconomic covariates, and λ_t (the conditional mean arrival rate of default measured in events per year) is a firm's default intensity. The firm may exit for other reasons, such as merger and acquisition or

[19] Compared to banks, insurers do not face the risk of a 'bank run' and claiming payments from them normally takes longer than withdrawing cash from banks.

[20] Investing in high-risk portfolios may yield higher returns than the normal underwriting business.

[21] To protect the interests of policy-holders, insurance firms are more likely to stop writing new business or transfer their business to other firms rather than becoming insolvent.

transfer of business to other firms, in which case the intensity is defined as φ_t. Thus the total exit intensity is $\varphi_t + \lambda_t$.

The forward default intensity is given by:

$$f_t(\tau) = exp\big(\alpha_0(\tau) + \alpha_1(\tau)X_{t,1} + \alpha_2(\tau)X_{t,2} + \ldots + \alpha_k(\tau)X_{t,k}\big) \quad (3)$$

and the forward combined exit intensity is defined as:

$$g_t(\tau) = f_t(\tau) + exp\big(\beta_0(\tau) + \beta_1(\tau)X_{t,1} + \beta_2(\tau)X_{t,2} + \ldots + \beta_k(\tau)X_{t,k}\big) \quad (4)$$

We use the pseudo-likelihood function derived by Duan et al. (2012) to estimate the forward default intensity. The details of the derivation of its large sample properties can be found in Appendix A of Duan et al.'s (2012) paper. In short, the pseudo-likelihood function for the prediction time τ is defined as

$$\mathcal{L}_\tau(\alpha, \beta; \tau_C, \tau_D, X) = \prod_{i=1}^{N}\prod_{t=0}^{T-1}\mathcal{L}_{\tau,i,t}(\alpha, \beta), \quad (5)$$

Our sample period goes from 0 to T and the frequency is annual. Firm i first appears in the sample at t_{0i} and τ_{Di} is the default time while τ_{Ci} is the combined exit time. During the sample period, if firm i exits because of default, then $\tau_{Di} = \tau_{Ci}$, otherwise $\tau_{Ci} < \tau_{Di}$. As previously explained, X_{it} are the covariates including common factors and firm-specific variables. The prediction horizon τ is measured in years with $\Delta t = 1$, and α and β are the model parameter sets for default and other exit processes, respectively.

According to the doubly stochastic assumption (also known as the conditional independence assumption), firms' default probabilities only depend on common factors and firm-specific variables and are independent from each other, i.e. the default of one firm will not influence other firms' exit probabilities.

The likelihood function $\mathcal{L}_{\tau,i,t}(\alpha, \beta)$ allows for five possible cases for firm i: in the prediction time period it can survive, default,[22] exit for other reasons (which in our sample means that the insurance firm transferred its business to other firms); it can also exit after or before the prediction time period:

$$\begin{aligned}\mathcal{L}_{\tau,i,t}(\alpha, \beta) = {} & 1_{\{t_{0i} \le t,\ \tau_{Ci} \ge t+\tau\}} P_t(\tau_{Ci} > t+\tau) \\ & + 1_{\{t_{0i} \le t, \tau_{Di} = \tau_{Ci} \le t+\tau\}} P_t(\tau_{Ci};\, \tau_{Di} = \tau_{Ci} \le t+\tau) \\ & + 1_{\{t_{0i} \le t, \tau_{Di} \ne \tau_{Ci},\ \tau_{Ci} \le t+\tau\}} P_t(\tau_{Ci};\, \tau_{Di} \ne \tau_{Ci}, \tau_{Ci} \le t+\tau) \\ & + 1_{\{t_{0i} > t\}} + 1_{\{t_{Ci} < t\}}\end{aligned} \quad (6)$$

where

$$P_t(\tau_{Ci} > t+\tau) = exp\left[-\sum_{s=0}^{\tau-1} g_{it}(s)\Delta t\right]$$

$$P_t(\tau_{Ci};\, \tau_{Di} = NG\tau_{Ci} \le t+\tau) = \begin{Bmatrix} 1 - \exp[-f_{it}(0)\Delta t], \ \text{when } \tau_{Ci} = t+1 \\ \exp\left[-\sum_{s=0}^{\tau_{Ci}-t-2} g_{it}(s)\Delta t\right] * \{\exp[-f_{it}(C_{it} - t - 1)\Delta t] - \exp[-g_{it}(\tau_{Ci} - t - 1)\Delta t]\}, \\ \text{when } t+1 < \tau_{Ci} \le t+\tau \end{Bmatrix}$$

$$P_t(\tau_{Ci};\, \tau_{Di} \ne \tau_{Ci}, \&\ \tau_{Ci} \le t+\tau) = \begin{Bmatrix} \exp[-f_{it}(0)\Delta t] - \exp[-g_{it}(0)\Delta t], \ \text{when } \tau_{Ci} = t+1 \\ \exp\left[-\sum_{s=0}^{\tau_{Ci}-t-2} g_{it}(s)\Delta t\right] * \{\exp[-f_{it}(\tau_{Ci} - t - 1)\Delta t] - exp[-g_{it}(\tau_{Ci} - t - 1)\Delta t]\}, \\ \text{when } t+1 < \tau_{Ci} \le t+\tau \end{Bmatrix}$$

The pseudo-likelihood function $\mathcal{L}_{\tau,i,t}(\alpha, \beta)$ can be maximised numerically to obtain the estimated parameters $\hat{\alpha}$ and $\widehat{\beta}$. Owing to the overlapping nature of this function, the inference is not immediately clear. For example, at time t_5 and the prediction horizon $\tau = 2$, firm A's default over the 2-year period starting 1 year ahead (t_4 to t_6) will be correlated with firm's B default in the next time period (t_6 in this case).

In addition, the pseudo-likelihood function can be decomposed into default and other exit processes which contain parameter sets α and β respectively, and each process can be further decomposed into different prediction horizon τ. As a result, the estimates $\hat{\alpha}$ and $\widehat{\beta}$ can be obtained at the same time.

$$\mathcal{L}_\tau(\alpha(s)) = \prod_{i=1}^{N}\prod_{t=0}^{T-s-1}\mathcal{L}_{i,t}(\alpha(s)), \ s = 0, 1, \ldots, \tau - 1 \quad (7)$$

$$\mathcal{L}_\tau(\beta(s)) = \prod_{i=1}^{N}\prod_{t=0}^{T-s-1}\mathcal{L}_{i,t}(\beta(s)), \ s = 0, 1, \ldots, \tau - 1. \quad (8)$$

5. Empirical results

5.1. Estimations results

In our model, the logarithm of forward default intensity has a linear relationship with the covariates:

$$\lambda_t(\tau) = \alpha_0(\tau) + \alpha_1(\tau)X_{t,1} + \alpha_2(\tau)X_{t,2} + \ldots + \alpha_k(\tau)X_{t,k}.$$

$X_{t,\,k}$ includes the following factors: GDP growth, real interest rate, real exchange rate, FDI, wholesale price change, underwriting profit, leverage, firm size, cash ratio, gross premium written change, reinsurance, incurred claims change, firm's growth, excess capital change, investment return, combined ratio, Herfindahl index, derivative dummy and organisational form. All covariates are lagged up to 3 years. For example, in the case of the one-year default prediction, all covariates are lagged by one year.

Table 4 shows the main estimation results based on the full sample going from 1985 to 2014. Other exit (i.e. transferring business to others) outputs can be found in Appendix (Table A.1. The original Solvency I Directive 73/239/EEC was amended by directive 2002/13/EC (non-life insurance) and became effective at the start of 2004. The policy changes were small (the absolute minimum amount of capital required has been increased and will be indexed in the future in line with inflation, whilst the method of calculating the required solvency margin remains essentially the same). However, the thresholds have been increased, and so has the power of supervisory bodies to intervene early to take remedial action when the interests of policy-holders are threatened. Therefore, as a robustness check, we also estimate the model over the subsample from 1985 to 2003; the results can be found in Appendix (Table B.1). In brief, most results stay the same, except that some macroeconomic variables such as the real exchange rate and FDI become significant owing to changes in the economic environment. Concerning firm-specific variables, claims change becomes

[22] Default events are collected from SynThesys Non-Life and include insolvent, in liquidation, placed in administration and dissolved.

Table 4
Estimations results.
Coefficients of constant, GDP growth, real interest rate, real exchange rate, foreign direct investment %, whole sale price %, credit provided by financial institutions %, underwriting profit, leverage, size, cash ratio, gross premium written %, reinsurance, incurred claims %, growth, excess capital, combined ratio, investment return, Herfindahl index, derivative dummy and organisational form based on full sample from 1985 to 2014. The model estimates the multi-period (up to 3 years' horizon) default probability of GI firms. In the following analysis, we calculate the default probability based on 1-year prediction. The values in parentheses in the table are the standard deviations.

Horizon Parameters	1	2	3
C	−15.952***	−24.965	−37.863
	(5.312)	(76.082)	(31.626)
GDP_growth	−0.053	0.041	0.116
	(0.053)	(0.489)	(0.214)
Real_IR	0.164***	0.284**	0.145
	(0.043)	(0.133)	(0.165)
Real_EXrate	0.004	0.010	0.019
	(0.009)	(0.209)	(0.075)
FDI %	0.020	−0.159	−0.121
	(0.073)	(0.679)	(0.248)
Wholesale price %	12.367***	16.385	25.995
	(4.708)	(50.366)	(22.396)
Credit by financial %	−3.641***	−0.291	−0.247
	(1.045)	(0.465)	(0.925)
PT	−3.781***	−3.745	−3.740
	(1.264)	(15.976)	(10.250)
Lev	0.523***	0.551	0.551
	(0.104)	(1.552)	(0.818)
Size	0.009	0.028	0.115
	(0.050)	(0.453)	(0.185)
CA	1.027***	1.049	−0.456
	(0.320)	(1.829)	(0.907)
GPW %	−0.789***	−0.565	−0.077
	(0.121)	(0.619)	(0.100)
Rein	0.822***	1.118	1.544
	(0.237)	(4.185)	(2.698)
Claim %	−0.023	−0.061	0.024
	(0.024)	(0.237)	(0.047)
Growth	0.025	0.118	0.021
	(0.118)	(0.906)	(1.134)
Eecess %	−0.388***	−0.450	−0.217
	(0.127)	(0.332)	(0.233)
InvR	−30.642***	−21.029	−2.692
	(4.766)	(161.676)	(85.657)
Combined ratio	0.003***	0.002	−0.004**
	(0.001)	(0.004)	(0.002)
Herfindahl index	0.397	0.763	1.759***
	(0.408)	(1.646)	(0.542)
Derivative dummy	0.627*	0.161	0.250
	(0.336)	(1.764)	(0.946)
Organisational form	0.970***	0.551	0.621
	(0.310)	(1.985)	(0.822)
Log-likelihood			−508.2668
No. of observations			5022

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

significant while the combined ratio and organisational form become insignificant. These are plausible findings since in the early years of the sample most firms were mutual firms, and therefore the organisational form does not matter. The results also suggest that mispricing (i.e. the combined ratio) is not the main reason for insolvency. Not surprisingly, the claims change variable is significant since natural disasters caused huge damage in the early 90s and more claims are one of the most important factors increasing the default probability of insurers.

Table 4 shows the results for the sample periods 1985 to 2014 with 1, 2, and 3 year horizons. Clearly, the annual data in our sample are not useful for predicting over periods longer than 1 year. However, the multi-period design of the model may be useful when high-frequency data are used - for example, for analysing publicly listed insurance firms. This also suggests that central banks should ask firms to submit data more frequently for better supervision.[23]

Next, we analyse the results based on the 1-year prediction. Most of them are in line with those of Adam et al. (2003). Leverage, underwriting profit, liquidity, reinsurance and organisational form[24] are significant factors both for assessing the insolvency risk of insurance firms and determining the quality of credit rating. On the other hand, firm size and growth are not significant.[25] Further, we find that macroeconomic and firm-specific factors (the change of credit provided by financial institutions, wholesale price change, investment profitability, combined ratio, and the usage of financial derivatives) are also important, and therefore should not be neglected. To our knowledge this is the first study documenting their key role in determining the insolvency risk of insurance firms.

Concerning macroeconomic variables, the real interest rate and the change in wholesale prices have a positive effect on default intensity that could lead to a higher default probability (PD). As for firm-specific variables, writing profitability and investment profitability are negatively correlated with default intensity. This suggests that high profitable firms are less likely to become insolvent. Further, our results are consistent with those of Titman and Wessels (1988), Frank and Goyal (2009), Carson and Scott (1997) and Bouzouita and Young (1998), who show that higher liquidity is associated with a higher credit rating. Therefore, firms holding more capital tend to have higher liquidity and a lower default probability. Moreover, the one-year PD shows that writing more premiums will lower an insurer's default probability. Firms with larger gross premium written will not only have cash inflows in the short term but also potential claims in the long term. The rapid growth of gross premium written may also have caused the mispricing problem (i.e. selling more policies at a cheap price - this is captured by the combined ratio) and the increase in the default probability of insurers. Finally, highly leveraged firms are less likely to survive during recessions and therefore normally have a higher PD.

There are also three more interesting findings. First, in general, large firms typically have a good reputation and therefore it is easier for them to obtain credit in the market. Bouzouita and Young (1998) find that large insurers are less likely to default. Our results suggest that firm size is not a significant determinant of the solvency of insurance firms.

Second, ad hoc structured reinsurance may reduce the credit risk exposure - for example, Adams (1996) shows that reinsurance improves the ability of the primary insurer to survive an external economic shock. However, we find a positive relationship between reinsurance and PD, which suggests that heavily reinsured firms are more likely to default. Insurers transfer part or all of their risk to other insurers through reinsurance and release capital reserves; in this way they have resources to write new business. Insurers are exposed to the counterparty risk of reinsures (e.g. when reinsurers are insolvent or run off, insurers will have to pay the claims to the policy-holders) and their fast-growing business may lead to higher potential losses in the future.

[23] In the UK, the Bank of England has been collecting quarterly data for more than 2 years; in the very near future, new data could be used in the model with multi-period prediction.

[24] 'Business Activitiy' in Adam et al. (2003).

[25] This could be due to the different datasets used. Ours covers 366 general insurance firms and data from 1985 to 2014. Adam et al. (2003) instead only consider 40 firms rated by A.M. Best plus 25 firms rated by S&P and include both general insurance and life insurance firms into the model.

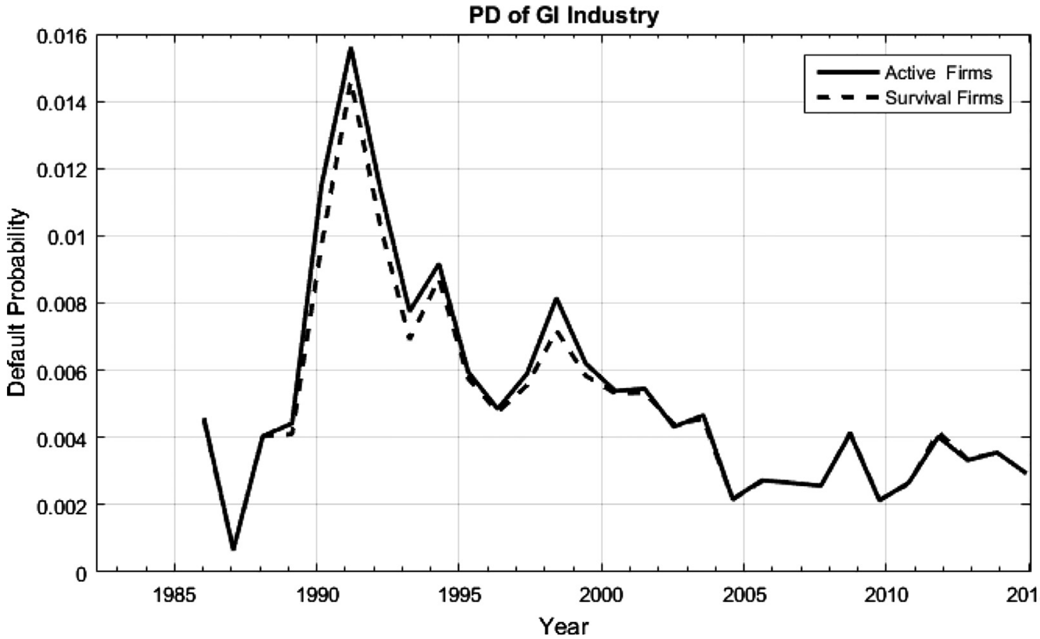

Fig. 1. PD of all firms. This figure plots the one-year default probability of all GI firms (straight line) and survival firms (dash line) from 1986 to 2014. We first predict the default probability of individual firms based on the parameters estimated by the doubly stochastic Poisson model. Then we calculate the median default probability given a state (active firms or survival firms) for each year.

Third, one important question is whether using derivatives increases the counterparty risk or is only useful for hedging. For example, derivatives could be used for hedging risk, but Shiu (2011) shows that this could also increase the exposure to counterparty risk. Our findings indicate that the use of derivatives may increase the probability of a firm becoming insolvent. This has important implications for assessing risk in this industry.

5.2. Overall probability of default for the general insurance industry

In this section, we estimate the default probabilities for all active firms as well as the survival firms. This is in fact the first study using historical default risk for all active firms based on their individual PD. We also consider the performance of insurance firms during natural disasters and financial distress times (that is, at times when insurers are vulnerable and more likely to default). Fig. 1 below shows the probability of default for the General Insurance industry from 1986 to 2014. The PDs are calculated using the full-sample parameter estimates.

Figs. 1 and 2 show that the PD of insolvent firms is much higher and fluctuates more compared to the whole GI industry. The highest PD of insolvent firms is about 0.07, which is almost six times that of the whole industry. For the GI industry, the PD peaks around the early 90s and then decreases until 2000; it is relatively low but increased sharply in 2008, at the time of the global financial crisis. The PD of insolvent firms peaks around 1990 and then decreases until 1996. There are two spikes in 2000 and 2003, before the 2008 global financial crisis. The average PD for default firms is 365 bps and 118 bps for the whole industry (97 bps for survival firms). The standard deviation for default firms is 0.0378, which is much higher than for the whole industry (0.0253) and for survival firms (0.0230). In general, default firms are more risky compared to the whole GI industry. These results indicate that, unlike banks, GI firms are more sensitive to natural disasters than a global financial crisis.

Fig. 3 shows a large PD spread between insolvent firms and the whole GI industry during the early 90s and a sharp rise in 2000 and 2003. It is generally positive before 2010, and it increases rapidly during the financial crisis, which indicates that all insolvent firms faced a worse financial situation and are more vulnerable than the whole GI industry. After 2008 it is much smaller or even negative.

To sum up, the default probability of the General Insurance industry varies over time and the PD of insolvent firms is more volatile than that of the survival firms. High PDs are usually found when there are disasters such as floods[26]; this indicates that, unlike other financial institutions, insurance firms are relatively stable but very sensitive to natural disasters. The high PDs around the time of the 2008 financial crisis suggest that the insurance and banking industries may be closely correlated (further research is

[26] 1990: The Burns' Day storm happened on 25-26 January 1990 across North-Western Europe and was one of the strongest European windstorms. It hit during the daytime and caused huge damage. There was severe flooding in England and insurers in the UK lost £3.37bn; it was the UK's most expensive weather event for insurers.1990-1991: There was an extremely cold winter in Western Europe. In the UK snow began to fall on the night of 7 December 1990 in the Midlands, Wales and the Pennines. Transport was severely disrupted and many people were trapped in their cars; moreover, there were power losses in many areas across the UK, and heavy rains and severe gales around Christmas and the New Year caused great damage to thousands of homes. There was more heavy snow in early February 1991 during the coldest winter since 1987. Temperatures stayed very low until 20 February.1998 Easter floods: Heavy rain started to fall on 9 April in the Midlands and then moved northwards causing severe floods. Thousands of housed were affected. 2000: Severe flooding across the UK.2007: Floods affected Gloucestershire, Yorkshire, Hull and Worcestershire and caused £6 million damage.2008: Morpeth floods. There was flooding in the Midlands and North East England. £40 million damage.2009: In February 2009 heavy snow in the UK resulted in £1.3 billion damage. In November 2009 heavy rain caused flooding in many areas across the UK. 2012: Great Britain and Ireland floods: most of UK experienced droughts in March, which was followed by the wettest April in 100 years. Heavy rains continued till July and resulted in flooding across the country. Widespread flooding and wind damage occurred in September, November, December, and January 2013. 2013: St. Jude storm; in October 2013 storms and strong winds (up to 160km/h) hit the south of England and Wales. East Coast Tidal Surge: in December 2013 strong northerly winds caused a large tidal surge which resulted in severe flooding of the coastal areas. 2013–14: United Kingdom winter floods: from December 2013 to February 2014 the south of England and Wales were hit by heavy rains and storms that caused flooding, power cuts and disruptions to transport.

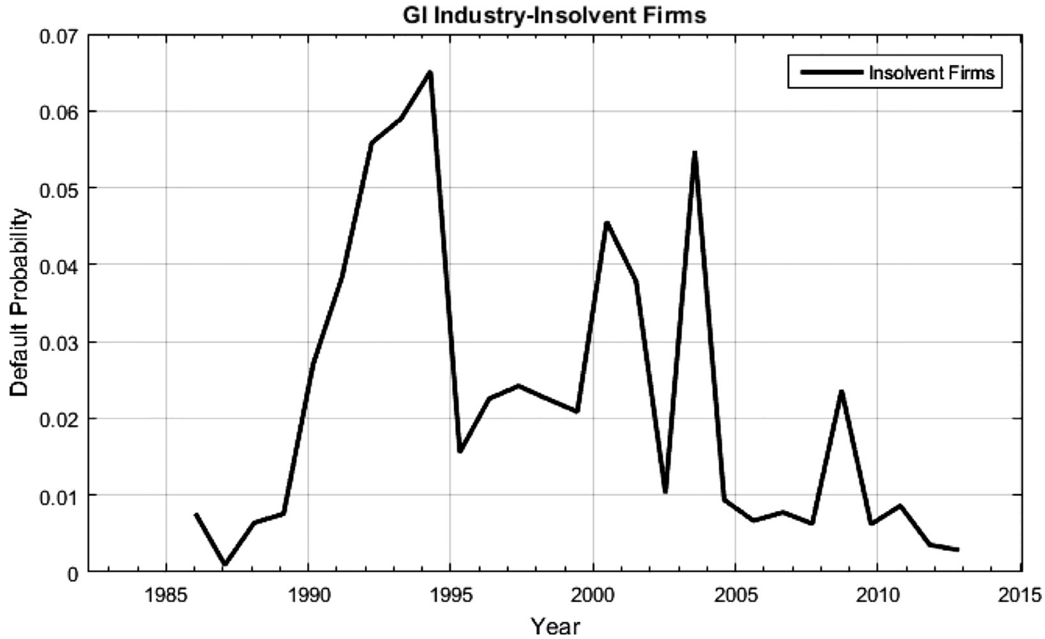

Fig. 2. PD of insolvent firms. This figure plots the one-year default probability of GI firms from 1986 to 2014. We first predict the default probability of individual firm based on the parameters estimated by the doubly stochastic Poisson model. Then we calculate the median default probability of all insolvent firms for each year.

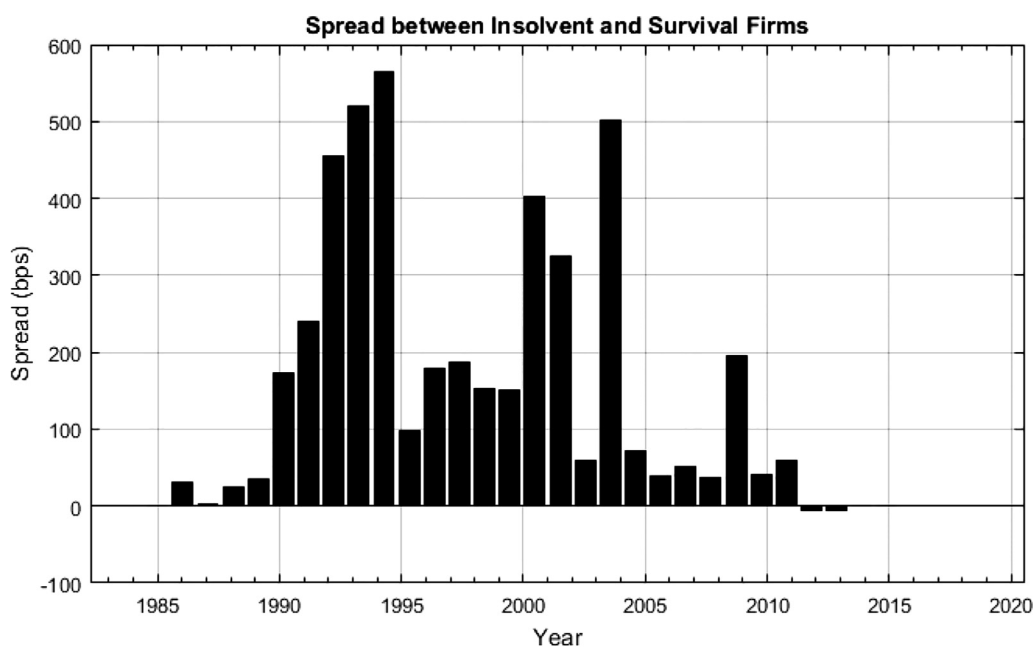

Fig. 3. PD spread between default and survival firms. This figure plots the one-year default probability of survival firms and the spread between survival and default firms from 1986 to 2014. We first predict the default probability of individual firm based on the parameters estimated by the doubly stochastic Poisson model. Then we calculate the average default probability given a state (insolvent firms or survival firms) for each year. The spread is calculated as the median PD of insolvent firms minus that of survival firms.

needed on this issue, which is beyond the scope of the present paper). Regulators should consider these interactions and be aware of the contagion effect in distress times.

5.3. Probability of default for different business lines

In general, insurance firms have business in different sectors and firms may change their main business line over time. In addition to business concentration, the change in the credit risk in different sectors has also important implication for the regulators' supervision and policy-making decisions. This crucial issue has been overlooked in the literature. Here we extend the credit risk analysis to the insurance firms' business lines.

On the basis of the gross premium written by each firm for different business lines, we classify insurance firms into 7 groups: 1. Accident & Health; 2. Motor; 3. Marine, Aviation & Goods in Transit; 4. Third-party Liability; 5. Financial Loss; 6. Household& Domestic All risks and Property; 7. Miscellaneous.

Around 1991, when natural disasters happened frequently, Motor has the highest default probability, with Accident & Health

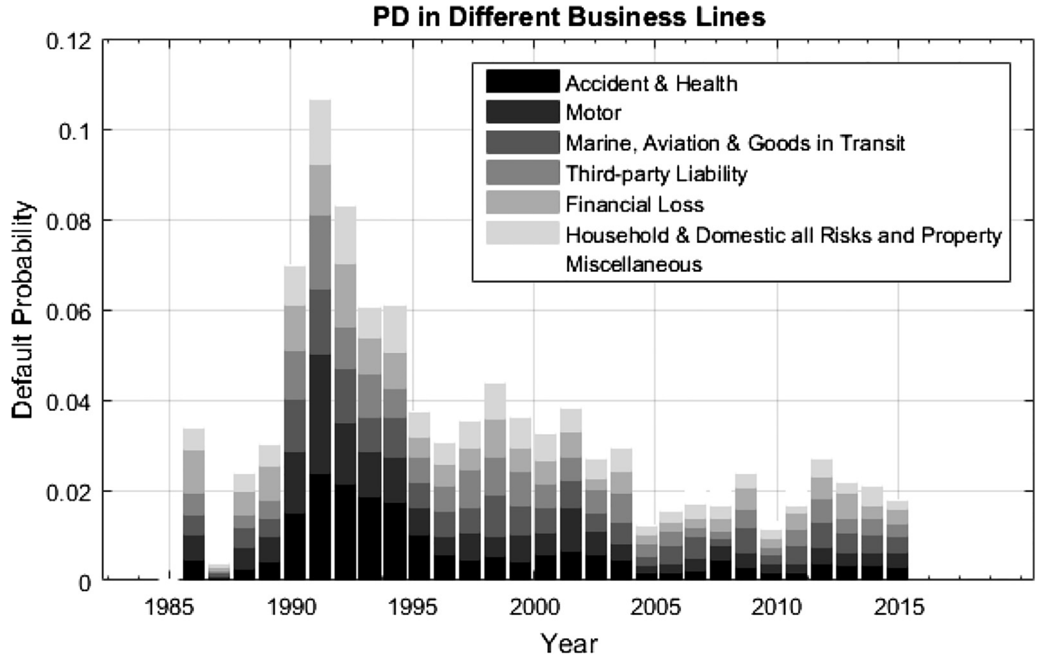

Fig. 4. PD of 7 groups. This figure plots the one-year default probability which is decomposed to 7 groups' PD from 1986 to 2014. We first predict the default probability of individual firm based on the parameters estimated by the doubly stochastic Poisson model. Then we take the median default probability given a business line (accident & health; motor; marine, aviation & goods in transit; third-party liability; financial loss; household & domestic all risks and property; miscellaneous) for each year.

having the second highest. Third-party Liability has the third highest, Household & Domestic All Risk and Property and Marine, Aviation & Goods in Transit have a slightly lower PDs, financial loss has the lowest. After 1991, the PDs of all groups are decreasing, while until 1996, the PDs are fluctuating around their average. The PDs of most groups exhibit an upward trend during the 2008 financial crisis, the exceptions being Accident & Health as well as Miscellaneous, which are relatively flat. Among all groups, the Financial Loss has the highest PD. After the financial crisis, Financial Loss and Marine, Aviation & Goods in Transit become the riskiest groups (Figs. 4 and 5).

Insurance firms are generally very vulnerable when natural disasters happen. Decomposing the PD of the insurance industry into different business lines reveals clear differences around the early 90s. Accident & Health, Household, Property, Motor, Transportation and Third-party Liability are the riskiest businesses because they are more likely to be exposed to catastrophes such as floods, earthquakes etc. However, the PDs of all business lines have the same upward trend in distress times except Accident & Health and Miscellaneous that are less correlated with the financial market. These findings suggest that regulators might want to consider the varying composition of the premium written by insurance firms when setting capital requirements. This forward-looking PD could give supervisors at the central bank a warning sign of a risky business, and under Solvency II the central bank could take action, for instance requiring firms to provide an additional buffer before they breach their MCR (minimum capital requirement) and SCR (solvency capital requirement).[27]

5.4. Default clustering and systemic risk

Since most insurance firms are non-public firms with a short history, very few of them are rated by credit rating agencies (e.g. Moody's, S&P, Fitch and A&M Best). Adam et al. (2003) analyse 65 non-life and life firms rated by A.M. Best and S&P, while our sample includes more than 300 GI firms. Using the estimation results from our model (see Table 4), we calculate PDs for all available firms (see Eq. (2)). We then extend the analysis to investigate the joint default risk. We compute pair correlations[28] of firms for different quantiles, and use the median value to obtain the default correlations. Previous studies such as Das et al. (2007) find strong default correlations among corporate obligors. It is interesting to establish whether insurance firms are likely to default jointly when their individual PDs are high. Also, high PD correlations may suggest that insurers are affected by common factors beside firm-specific factors.

We calculate the average pair PD correlations of all firms within different groups (from low risk 0%–20% to high risk 80%–100%) based on data for the period 1985–2014. The highest PD correlations are found in the 0%–20% quantile, and the second highest in the 20%–40%. The fact that the highest correlation is that between insurers with the lowest PD suggests that when insurance firms are less exposed to risk there is a more important role for common factors, in our case macroeconomic factors such as the credit supply and wholesale price changes. Insurers within the highest 80%–100% quantile have the third highest PD correlation, which indicates that their credit risk is affected by both common and firm-specific factors. The observed pattern for PD correlations for different quantiles supports our choice of considering macroeconomic factors as well as firm-specific factors. Overall, our empirical results are in line with those of Bell and Keller (2009), who show that insurers are less interconnected than banks and there is a lower contagion effect among them. The PDs for the 20% quantile has the highest correlation (0.2111). The lowest correlation is −0.0170, while the PD correlation for the group '40%–60%' is much

[27] The SCR and MCR act as trigger points in the 'supervisory ladder of intervention' introduced by Solvency II.

[28] The default correlations are estimated by calculating the pair PD correlations across firms in each quantile. A similar approach is taken by Duan and Miao (2016), who estimate the joint default probability on the basis of the individual firm's default probability that has been obtained first using the doubly stochastic Poisson model.

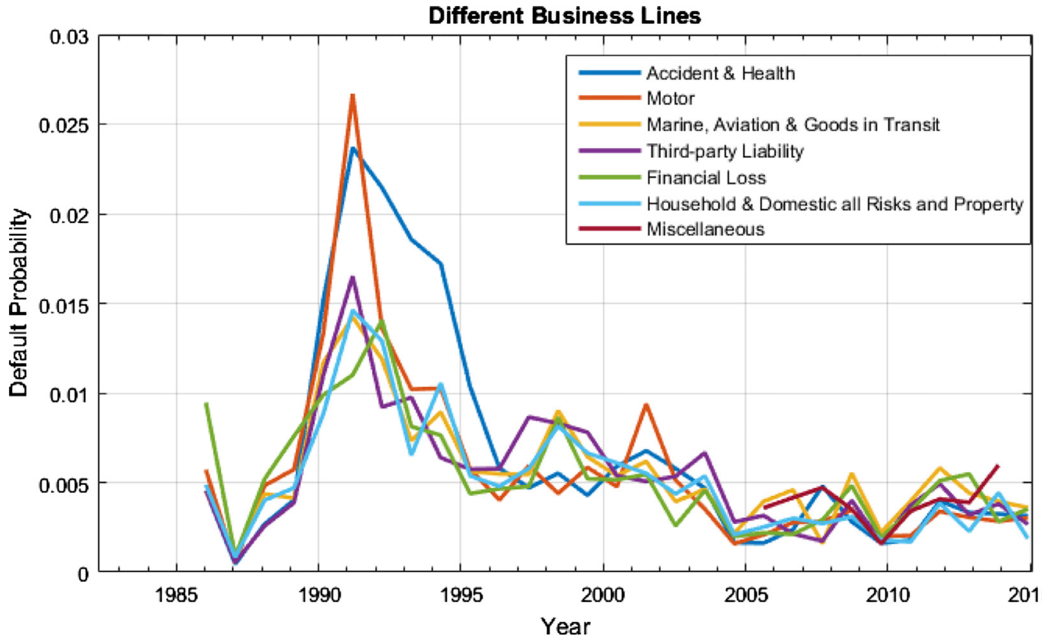

Fig. 5. PD of 7 groups. This figure plots the one-year default probability of 7 groups: Accident & Health, Motor, Marine, Aviation & Goods in transit, Third-party liability, Financial Loss, Household & Domestic all risks and property, and Miscellaneous from 1986 to 2014. We first predict the default probability of individual firm based on the parameters estimated by the doubly stochastic Poisson model. Then we take the median default probability for a given business line for each year.

higher (−0.0095), and the PD correlation for the group '20%–40%' is slightly higher (0.1233). The '80%−100%' group has the third largest PD correlation (0.0315); this points to some default clustering. The highest PD correlation is found for the group '0%−20%', which suggests that in safe times most insurance firms are in a good financial situation. Overall, the results imply that systemic risk within general insurance firms is low.

5.5. Reinsurance and default risk

Reinsurance is a pure hedging contract that enables primary insurers to transfer risks to third parties (i.e. reinsurers receive a share of annual premia written from primary insurers to compensate them for potential loss events). Previous papers show that corporate hedging decisions such as reinsurance affect the strategic performance of firms (Harris and Raviv, 1991; Adam et al., 2007). Aunon-Nerin and Ehling (2008) highlight that indemnity contracts such as reinsurance contracts are pure hedging instruments. Harrington and Niehaus (2003) argue that reinsurance is important because solvency risk matters to both policy holders and regulators. Upreti and Adam (2015) find that reinsurance enables primary insurers to have sufficient risk capacity for planning and pricing new business lines. Therefore, insurers can be exposed to new risks through risk financing as well as reinsuring activities.

As already discussed, insurers with a high reinsurance ratio usually also have a high PD. Therefore the counterparty risk of reinsurance will increase the insolvency risk of primary insurers, and not surprisingly, under Solvency II, reinsurance assets[29] are listed separately from cash and financial assets in an insurance firm's balance sheet; also, technical provision (i.e. provisions for expected future claims) of reinsurance has been incorporated into Solvency II as part of liabilities. Reinsurance activities link different insurers together and represent a contagion channel in the system in distress times; consequently, the performance of reinsurance firms (firms buying reinsurance) is very important for the whole general insurance industry.

Next, we investigate the performance of firms when they use the reinsurance market. We first classify them into different groups based on the percentage of reinsurance they accept relative to their total written gross premium, and then we analyse the credit spread of firms who accepted reinsurance across the different groups.

Reinsurance firms play a crucial role in the general insurance market. The orange line in Fig. 6 shows that the percentage of firms in each size group changes over time. The total percentage of firms accepting reinsurance peaked in 1988 and decreased afterwards. Most firms accept less than 20% reinsurance, and this percentage has been decreasing since 1987. Less than 50% of firms have accepted 20% to 80% reinsurance, most of the time, in the last 30 years. There are more than 15% of firms in the upper 20% group between 1996 and 2005, when this percentage peaked. The maximum spreads for each group are 67 bps, 111 bps, 66 bps, 102 bps, 40 bps, and 38 bps, respectively, and their standard deviations 0.0017, 0.0031, 0.0022, 0.0032, 0.0018, and 0.0011. For each group, we calculate the credit spread between firms accepting reinsurance and firms not accepting it.

Fig. 6 shows that the lowest 20% firms have a negative spread in most periods, except during the early 90s, vis-à-vis the firms that do not use the reinsurance market. This may indicate that firms that are less involved with the reinsurance market often have good creditworthiness and take reinsurance as part of their business plan.[30] By contrast, firms accepting 20% to 40% reinsurance can have either positive or negative spreads at different points in time in the sample period. During the financial crisis, their spread vis-à-vis firms not accepting reinsurance is positive. For the group of firms accepting between 40% to 60% and 60% to 80% reinsurance, the spread is positive most of the time, except during the 90s. Finally, for the group accepting more than 80% reinsurance the spread peaked during the early 90s (at the time of the Burns' Day Storm), and became relatively small during the financial crisis, and even negative (−0.0016) in 2008. This may reflect the fact that, for the pure reinsurance firms, their risk management strategy is aimed at reducing potential losses during distress times.

[29] Reinsurance assets here refers to ceded reinsurance assets that are by definition only those of the cedant associated with ceded reinsurance contracts.

[30] Through reinsurance, firms will have less liability, fewer reserves requirement, but release more capital to write new business or investment in other products.

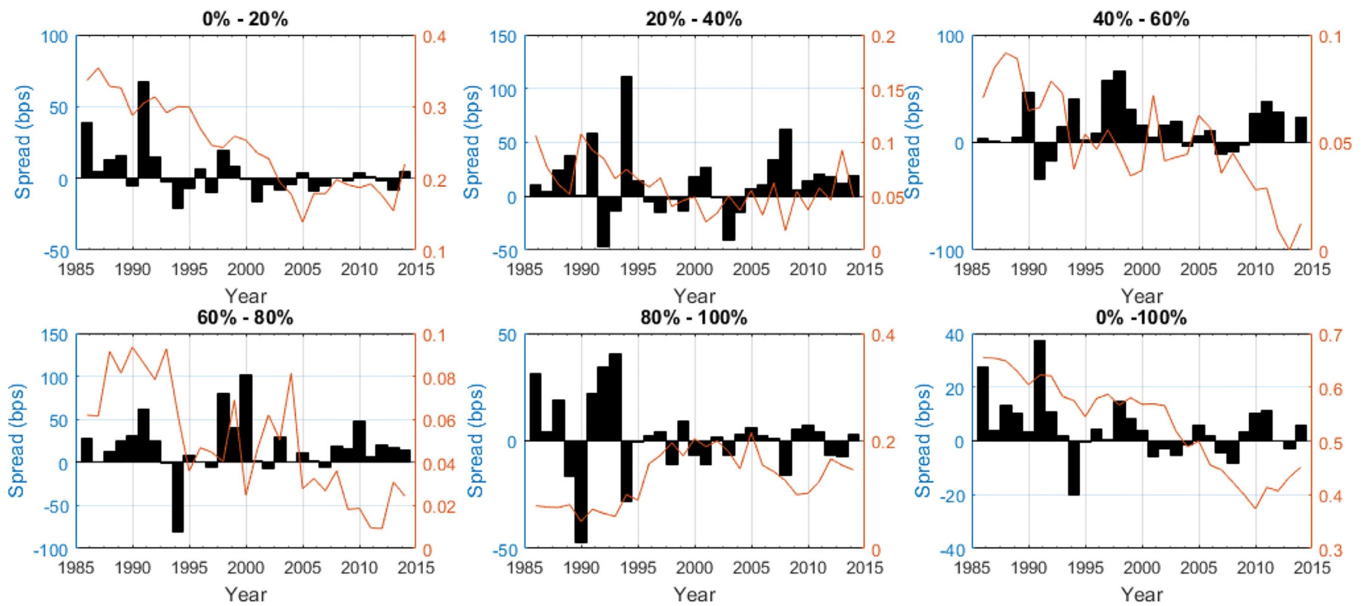

Fig. 6. Credit spread when taking Reinsurance. Credit spread between firms accepting reinsurance and firms not accepting reinsurance at different levels (full sample calibration). Orange line: percentage of firms with reinsurance accepted at certain level; black stack: credit spread.

In our sample, for all firms taking reinsurance (group 0%−100% in Fig. 6) compared to firms not taking reinsurance, there are 19 years with a positive spread, and 10 years with a negative one. The results imply that firms accepting reinsurance have a higher default probability, especially when natural disasters happen (i.e. the Burns' Day Storm in the early 90s).

However, firms taking reinsurance performed well during the 2008 financial crisis. Four groups have a negative spread and other two have a nearly zero spread (0.0062 in group 20%−40% and 0.0018 in group 60%−80%). This is a new and important result. Firms taking reinsurance may choose a more determined risk management strategy and therefore buy good-quality reinsurance to help reduce risk at times of financial distress. Doherty and Tinic (1981) find that reinsurance contracts make primary insurers manage cash flow volatility more effectively, and result in better future underwriting ability, and lower insolvency probability. Our results show that, on the other hand, reinsurers also benefit from indemnity contracts resulting in lower default probabilities.

Overall, these findings suggest that firms taking reinsurance have a higher insolvency risk than those not doing so, and are more vulnerable when natural disasters happen. However, reinsurers outperform other insurers during financial crises. This may be due to the fact that their risk management strategy aims at reducing potential losses during distress times.

In addition, under Solvency II, reinsurance assets are calculated on a best-estimate basis, which means that their market value is the discounted value of future cash flows; therefore, the default probability of reinsurers plays an important in this estimate. Our results clearly show that the insolvency risk of reinsurers depend on how much reinsurance they take. Thus, when estimating the future cash flows of reinsurance assets, the varying default probability of reinsurers should be taken into account. Given the fact that most general insurance firms are not rated, our model could provide an alternative way for policy-makers to measure the insolvency risk of reinsurers and the market value of reinsurance assets.

6. Conclusions

This paper analyses the insolvency risk of general insurance (GI) firms in the UK using a unique dataset; specifically, a reduced-form model is estimated that considers both insolvency and other types of exit such as transferring business. Our results show that most traditional risk factors (for example, interest rates, liquidity, profitability, leverage etc.) are significant determinants of the insolvency risk of insurers. However, in contrast to other studies, we show that macroeconomic factors (wholesale price and credit provided by financial institutions) and firm-specific factors (growth premium written, reinsurance, usage of derivatives and organisational form) are also crucial for assessing the credit risk of GI firms. This represents new and interesting evidence.

Further, we investigate the credit risk of firms with different business lines. We show that in the early 90s, owing to natural disasters, the group Motor had the highest credit risk, while after the financial crisis Marine, Aviation & Goods in transit and Financial Loss became the riskiest sectors. Our time-varying estimates of PD could be used as an early warning for risky sectors to which regulators might want to apply more stringent minimum capital requirements before firms breach their MCR and SCR. We also show that the joint default correlation for different insurance firms is low, but there is a default clustering.

Finally, our findings indicate that different reinsurance levels affect the insolvency risk of insurance firms. Primary insurers can lower their insolvency risk by buying reinsurance contracts from reinsurers. Moreover, the latter, despite taking on risk from primary insurers through this process, appear to have an even lower insolvency risk during periods of financial distress. The default probability of reinsurers can be used by policy-makers for the estimation of the market value of reinsurance assets of GI firms under the new Solvency II.

Appendix A. Multi-period other exit estimation outputs-full sample

Horizon Parameters	1	2	3
C	1.762	−2.849	1.885
	(41.041)	(10.496)	(15.594)
GDP_growth	−0.054	−0.013	−0.007
	(0.160)	(0.044)	(0.073)
Real_IR	−0.074	−0.006	0.030
	(0.270)	(0.073)	(0.127)
Real_EXrate	0.021	0.017	0.011
	(0.088)	(0.022)	(0.034)
FDI %	−0.024	−0.030	−0.087
	(0.188)	(0.063)	(0.116)
Wholesale Price %	−8.256	−2.653	−7.135
	(33.567)	(8.757)	(12.226)
Credit by Financial %	−0.566	−1.753***	−1.243
	(1.121)	(0.676)	(1.432)
PT	−2.803	−0.435	−0.931
	(14.372)	(3.629)	(6.189)
Lev	0.206	0.310	0.290
	(1.733)	(0.404)	(0.686)
Size	−0.035	−0.002	0.025
	(0.130)	(0.040)	(0.064)
CA	−1.277	−1.353***	−1.017***
	(0.862)	(0.306)	(0.332)
GPW %	−0.074	−0.042	−0.071
	(0.178)	(0.054)	(0.111)
Rein	0.903	0.701	0.565
	(2.607)	(0.750)	(1.477)
Claim %	0.054	0.059***	0.048***
	(0.045)	(0.010)	(0.009)
Growth	−0.297	−0.359*	−0.376
	(0.770)	(0.214)	(0.391)
Eecess %	−0.024	−0.021	−0.038
	(0.116)	(0.057)	(0.078)
InvR	9.165	5.986	3.839
	(141.332)	(35.631)	(64.311)
Combined Ratio	0.008***	0.008***	0.007***
	(0.002)	(0.001)	(0.002)
Herfindahl index	1.066***	1.328***	1.129***
	(0.292)	(0.261)	(0.250)
Derivative Dummy	0.736***	0.736***	0.611***
	(0.229)	(0.226)	(0.211)
Organisational Form	0.073	−0.063	−0.172
	(1.279)	(0.354)	(0.586)
Log-likelihood			−508.2668
No. of observations			5022

Note: Multi-period default estimation outputs of other exit for 1,2, and 3-year time horizons. Coefficients of constant, GDP growth, real interest rate, real exchange rate, foreign direct investment %, whole sale price %, credit provided by financial institutions %, underwriting profit, leverage, size, cash ratio, gross premium written %, reinsurance, incurred claims %, growth, excess capital, combined ratio, investment return, Herfindahl index, derivative dummy and organisational form based on the full sample from 1985 to 2014. The values in parentheses in the table are the standard deviations.

*Significant at 10%.

**Significant at 5%.

*** Significant at 1%.

Appendix B. Multi-period default estimation outputs – 1985–2003

Horizon Parameters	1	2	3
C	−28.819***	−36.933	−52.267*
	(9.384)	(92.437)	(29.640)
GDP_growth	−0.080	0.083	0.077
	(0.106)	(0.386)	(0.100)
Real_IR	−0.158**	0.195	−0.151
	(0.078)	(0.277)	(0.182)
Real_EXrate	0.026**	0.024	0.036
	(0.013)	(0.234)	(0.059)
FDI %	0.597**	−0.003	0.137
	(0.245)	(1.897)	(0.774)
Wholesale Price %	25.502***	26.070	37.479
	(8.829)	(65.336)	(23.248)
Credit by Financial %	−5.934**	−0.681	−0.270
	(2.323)	(1.148)	(0.696)
PT	−5.387***	−5.391	−4.779
	(1.283)	(14.942)	(6.642)
Lev	0.468***	0.513	0.506
	(0.116)	(1.531)	(0.537)
Size	0.098	0.140	0.284*
	(0.067)	(0.551)	(0.148)
CA	1.996***	1.977	0.493
	(0.434)	(3.151)	(1.230)
GPW %	−0.949***	−0.910	−0.305
	(0.147)	(0.802)	(0.216)
Rein	1.014***	1.301	1.800
	(0.298)	(3.800)	(2.068)
Claim %	−0.074*	−0.152	0.009
	(0.043)	(0.381)	(0.089)
Growth	−0.008	0.118	0.026
	(0.156)	(1.030)	(0.935)
Eecess %	−0.299**	−0.364**	−0.121
	(0.131)	(0.158)	(0.111)
InvR	−32.469***	−21.424	−0.056
	(5.148)	(148.534)	(55.823)
Combined Ratio	0.002	0.000	−0.018***
	(0.001)	(0.001)	(0.007)
Herfindahl index	0.139	0.434	1.694***
	(0.458)	(1.739)	(0.595)
Derivative Dummy	0.736**	0.393	0.443
	(0.351)	(1.436)	(0.746)
Organisational Form	0.136	0.207	0.211
	(0.727)	(0.748)	(0.779)
Log-likelihood			−248.0849
No. of observations			3429

Note: Multi-period default estimation outputs of default for 1, 2, and 3-year time horizons. Coefficients of constant, GDP growth, real interest rate, real exchange rate, foreign direct investment %, whole sale price %, credit provided by financial institutions %, underwriting profit, leverage, size, cash ratio, gross premium written %, reinsurance, incurred claims %, growth, excess capital, combined ratio, investment return, Herfindahl index, derivative dummy and organisational form based on the full sample from 1985 to 2003. The values in parentheses in the table are the standard deviations.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Appendix C. Multi-period default estimation outputs

Horizon Parameters	1	2	3
C	−15.958***	−24.967	−37.863
	(−5.312)	(−76.076)	(−31.626)
GDP_growth	−0.053	0.041	0.116
	(−0.053)	(−0.489)	(−0.214)
Real_IR	0.164***	0.284**	0.145
	(−0.043)	(−0.133)	(−0.165)
Real_EXrate	0.004	0.01	0.019
	(−0.009)	(−0.209)	(−0.075)
FDI %	0.02	−0.159	−0.121
	(−0.073)	(−0.679)	(−0.248)
Wholesale Price %	12.372***	16.387	25.995
	(−4.708)	(−50.363)	(−22.396)
Credit by Financial %	−3.640***	−0.291	−0.247
	(−1.045)	(−0.465)	(−0.925)
PT	−3.781***	−3.745	−3.74
	(−1.264)	(−15.975)	(−10.25)
Lev	0.523***	0.551	0.551
	(−0.104)	(−1.551)	(−0.818)
Size	0.009	0.028	0.115
	(−0.05)	(−0.453)	(−0.185)
CA	1.027***	1.049	−0.456
	(−0.320)	(−1.829)	(−0.907)
GPW %	−0.789***	−0.565	−0.077
	(−0.121)	(−0.619)	(−0.100)
Rein	0.822***	1.118	1.544
	(−0.237)	(−4.185)	(−2.698)
Claim %	−0.023	−0.061	0.024
	(−0.024)	(−0.237)	(−0.047)
Growth	0.025	0.118	0.021
	(−0.118)	(−0.906)	(−1.134)
Eecess %	−0.388***	−0.45	−0.217
	(−0.127)	(−0.332)	(−0.233)
InvR	−30.644***	−21.03	−2.692
	(−4.766)	(−161.663)	(−85.657)
Combined Ratio	0.003***	0.002	−0.004**
	(−0.001)	(−0.004)	(−0.002)
Herfindahl index	0.397	0.763	1.759***
	(−0.408)	(−1.645)	(−0.542)
Derivative Dummy	0.628*	0.162	0.25
	(−0.335)	(−1.759)	(−0.946)
Organisational Form	0.969***	0.551	0.621
	(−0.310)	(−1.985)	(−0.822)
Log-likelihood			-508.2668
No. of observations			5022

Note: Multi-period default estimation outputs of default for 1,2, and 3-year time horizons. Coefficients of constant, GDP growth, real interest rate, real exchange rate, foreign direct investment %, whole sale price %, credit provided by financial institutions %, underwriting profit, leverage, size, cash ratio, gross premium written %, reinsurance, incurred claims %, growth, excess capital, combined ratio, investment return, Herfindahl index, derivative dummy and organisational form based on the full sample from 1985 to 2014. The values in parentheses in the table are the standard deviations.

The derivative dummy is defined as being equal to 1 for insurance firms using derivatives for hedging, and 0 for the others.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

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