Exploring the Determinants of Credit Risk of General Insurance Firms in the United Kingdom

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ABSTRACT

This paper apply reduced form model to access the credit risk of general insurance (non-life) firms in the United Kingdom. This paper extends previous research of credit risk of insurance industry in UK market by using a larger database and more risk factors. Both macroeconomic and firm-specific factors are taken into consideration in assessing the credit risk of general insurance firms. In addition, we firstly consider both insolvency and other exit like transferring business when modelling the default process for insurance firms to avoid censoring bias. Our research firstly applies 20 years regulation data of 515 firms to assess credit risk of UK insurance industry. With the support by Bank of England, we study and identify insolvent events from different data sources. After exploring the sources causing insolvency, we analyse the credit risk of insurance firms with different business lines. Then we analyse system risk in the GI firms. At last, we further study the relationship between reinsurance assumed and credit risk of GI firms. The empirical results may provide implications to regulators of the GI firms' supervision under the coming *Solvency II*.

Key words: Insolvent; Doubly Stochastic; Insurance; Reinsurance

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1. Introduction

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

Comparing to banking industry, insurance industry is relatively stable, but the risk among insurance firms cannot be ignored. Unlike banks, insurers do not accept deposits from customer, they do not face the risk of a sudden shortage in liquidity which caused by a bank-run. Also, insurers often hold more long-term liabilities rather than short-term liabilities. In addition, Bell and Keller (2009) find that insurers are less interconnected than banks and result in lower contagion effect among insurers. After financial crisis, Janina and Gregor (2015) argue that insurance firms are becoming more similar to banks and will contribute to the systemic risk of the financial system. Furthermore, the study by Geneva Association (2010) indicates that the insurance industry would raise the systemic risk of the financial sector if insurers heavily engaged in derivatives trading off balance sheet or they mismanaged short-term financing activities.

It's very difficult to access the credit risk of insurance firms because there have been very few firms which became insolvent before choosing to transfer their business to other insurance firms or just stop writing new business and 'run-off'. Alternatively, third-party rating agencies may provide a good view of insurance firms' financial condition. However, the main problem of external rating agencies is that not all insurance firms are being rated and the ratings normally stay stable for many years. Also different rating agencies like *A M Best, Standard & Poor's, Moody's* and *Fitch* have their own rating methodology and labelling systems. Sometimes credit rating of corporate bonds issued by the firm is used when there is no rating for the firm's financial strength.

Under *Solvency II*, credit risk means the risk of loss, or of adverse change, in the financial situation, resulting from fluctuations in the credit standing of issuers of securities,

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

counterparties and any debtors to which a *Solvency II* undertaking is exposed, in the form of counterparty default risk, or spread risk, or market risk concentrations[2].

In this paper, we consider the credit risk of insurance firms consists of three parts. Firstly, it's the credit quality of firms' investment portfolios. In our paper, we use investment returns to measure the performance of investment portfolios. Secondly, the counter-party risk through reinsurance activity and the purchasing of derivative contracts. High reinsurance ratio and holding derivative contracts increase the firms' credit risk exposure. Reinsurance ratio and dummy variable for the usage of derivative contract are applied in our model. Thirdly, it's the direct default risk of insurers themselves when their liabilities are less than their assets and therefore become insolvent. The firms' financial health is measured by the leverage, profitability, solvency and liquidity ratios. We also take the firms' size, growth and claims volatility into consideration.

Our paper firstly consider different firm's exit situation which including insolvency and transferring business. And we find new risk factors, both macroeconomic and firm-specific variables, affect insurers' insolvency like interest rate, whole sale price change, credit supply change, usage of financial derivatives and combined ratios. When assessing the profitability of insurers, we look at profit from both traditional underwriting business and investment activities.

2. Literature Review

The insurance industry is largely believed to be in more stable condition than other industries such as the banking industry and there might be several reasons for this difference. For example, 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 to the stability of the financial system overall. Das et al., (2003) suggest that the insurance industry is more stable because insurers do not suffer from a 'bank run', and insurance policies cancellation process takes longer than closing a bank account. Furthermore because of larger premium, policy holders would suffer a loss in the case of a policy cancellation.

However, if on one side, the insurance industry appears to be more stable than other industries, on the other hand, during the recent years, with the fast growth of financial

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

derivatives, the insurance firms appear to be also more engaged with banks[3]. 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 like catastrophe bonds to transfer the catastrophe risk to other investors. Also, investment in asset backed securities has increased. As a result of this, as pointed out by Baluch et al (2011), insurance firms are becoming more vulnerable during the crisis. This is also in line with studies such as Das et al., (2003) who find that the linkage through reinsurance activities may cause several primary insurance firms to fail at the same time and Acharya et al., (2015) who suggest that large insurance firms are more likely to invest in high-risk assets because they are correlated with different financial institutions. In this paper we aim to contribute to assess the vulnerability of the UK insurance industry. To the best of our knowledge, this is the first paper to address this issue relatively to UK.

One of the most recent papers on UK non-life insurance industry is Shiu (2011) who uses data from 1985 to 2002 to investigate the relationship between reinsurance and capital structure. Shiu (2011) shows that insurers with higher leverage tend to purchase more reinsurance, and insurers with higher reinsurance dependence tent to have a higher level of debt. Using the same database, Shiu (2007) shows that insurer's size, liquidity, interest rate risk exposure, line of business concentration and organizational 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 based on a sample of 65 firms dating from1993 to 1997. They find mutual insurers are generally assigned higher ratings than non-mutual insurers. Also liquidity and profitability have a significantly positive effect on the ratings.

The majority of prior credit risk modelling studies has concentrated on banking industry. In our paper, we employ the reduced form model to measure credit risk of general insurance firms in the United Kingdom.

[3] Insurance firms are more engaged with banks through trading financial derivatives and other investment activities.

3. Data and Covariates

Firm-specific variables are collected from *SynThesys Non-Life*[4]. *SynTheesys Non-Life* consists of FSA data (it's regulated under Prudential Regulation Authority, Bank of England now) of non-life annual return regulatory data. This database allows quick access to FSA return data for current year and historical years back to 1985. Over 400 companies are included in the current *SynThesys Non-Life* system and the data include statement of solvency, components of capital resources, statement of net assets, calculation of capital requirement, analysis of admissible assets, liabilities, profit and loss account, analysis of derivative contracts, summary of business carried on, technical account, analysis of premiums, analysis of claims, analysis of expenses and analysis of technical provisions etc. Also, there are approximately 180 ratios currently included in *SynThesys* enabling calculations to be included directly into reports, 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. Additionally to this, in the UK market, instead of being insolvent, most general insurance firms go into 'Run-Off' (i.e. stop writing new business and wait the financial condition turn better or transfer their business to others). All the credit events in our paper are hand collected from *Appendix D: Company Changes, Transfers, Mergers of SynThesys Non-Life UserGuide version 10.1*[5]*, PwC - Insurance insolvency*[6] *and Financial Services Compensation Scheme*[7] and the final list is further discussed with technical specialists and senior supervisors from Insurance Division at the Bank of England. Macroeconomic data are obtained from the *World Bank*.

Before using the data, first, we remove firms without at least one-year balance data for all the variables. This is because these firms cannot be used to calibrate the model. We also remove firms which de-authorized without any reasons. Firms which could be de de-authorized by many reasons like merger & acquisition, insolvency or simply run-off and disappear. If the model fails to take other types exit (i.e. except insolvency) into consideration, firms exited due to other reasons will be treated like survival firms. As the result, this will affect the calibration of the model. Further discussion about the different

[4] From *Standard & Poor's*
[5] Updated on November 2014
[6] http://www.pwc.co.uk/services/business-recovery/insights/insurance-insolvency-case-updates-pwc-uk.html
[7] http://www.fscs.org.uk/what-we-cover/products/insurance/insurance-insolvencies/

types of firms' exit can be found in the model section. At the end, we have 363 firms left with 14 firm-specific variables and 6 macroeconomic variables in our dataset spanning from 1986 to 2014. We have 35 firms which became insolvent during our sample period and 45 firms exited due to other reasons like transferring their business to other firms.

To lessen the effect of outliers, we winsorize some firm-specific variables. For example, we cap reinsurance ratio and leverage ratio at 95 percentile value and remove the lower 5 percentile value. Also we cap liquidity ratio, profitability ratio, growth premium written change, claim change and excess capital ratio at 99 percentile value and remove the lower 1 percentile value. The summary statistics and correlation matrix of firm-specific values and macroeconomic values are reported in Table 1, Table 2 and Table 3.

3.1 Covariates

Following the main literature[8], we choose firm-specific variables: leverage (Net Technical Provisions /Adjust Liquid Assets, *SynThesys* Appendix K: Ratio Definitions R12), profitability (underwriting profit to Total Assets), growth (Change in 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 change (The change of net claims incurred), capital (The change of excess capital resources to cover general business CRR), liquidity (Cash/Total Asset: The ratio of the sum of cash and short-term investments to the total assets), gross premium written (The annual change of gross premium written), combined ratio (Incurred Claims + Management Expense) / Gross Premium Written), Line-of-Business Concentration (Herfindahl index), organizational form (mutual or non-mutual firm) and derivative dummy variable (Derivative dummy defined based on *SynThesys* form 17, i.e. whether the sum of form 17 is zero or not). In addition, we also include UK macroeconomic variables, like GDP growth, change of wholesale price index (2010=100), change of foreign direct investment, net inflows, real interest rate, real effective exchange rate index (2010=100) and change of credit provided by financial intuitions (% of GDP) from *the World Bank*.

Leverage:

Higher leverage may have an adverse effect of insurance firms' performance. Insurers with high leverage will have a potential adverse effect of their underwriting performance and

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

insurer's capital is more vulnerable to economic shocks. In addition, Adams et al., (2003) find that insurers with lower financial leverage will be more likely to be assigned a higher credit rating. Previous studies like Brotman (1989) and Pottier (1997, 1998) also regard financial leverage have a negative relationship with insurance firms' capital structure.

Profitability:

Profitability indicates the ability of insurance firms using surplus to develop current business and generate new business. Higher profitability ratio means the insurance firm has a good control of managing expenses and setting competitive premium rates. Also Titman and Wessels (1988) and Frank and Goyal (2009) suggest that high profitable firms would have a lower debt ratio which represents a lower probability of credit risk.

Firm Growth:

Normally, positive growth ratio could be a signal of good financial condition for a firm. But for issuers with significant new business growth could be caused by poor underwriting standards and mispricing strategy (Adams et al., 2003). And Borde et al. (1994) and Pottier (1997) find that this will lead to greater uncertainty about the capital reserve risk for insurance firms. Also Frank and Goyal (2009) find that firms with high growth ratio would face more debt-related agency issues and higher associated cost.

Firm Size

Prior study like Bouzouita and Young (1998) find large insurers are less likely to become insolvent. Large insurers normally would have economies of scale and scope, and since prominent market shares and the higher probability to be rated (Adams et al. (2003)) have lower financing costs comparing to small insurers.

Reinsurance:

Berger et al. (1992) state that there're two types traditional reinsurance activity which involving a direct insurer ceding all or ceding part of its assumed underwritings to another insurance company. Insurance firm transfer part of their risk to third parties by reinsurance and result in lowering uncertainty of their future losses and reducing their capital reserves. Adams (1996) suggest reinsurance improve the ability of the primary insurer to survival 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.

Claims Growth[9]*:*

In insurance industry, incurred claims is the amount of outstanding liabilities for policies over a given valuation period. A significant increase of net claims incurred may lead to liquidity risk of an insurer and finally if the insurer fell to raise enough capital, it may become insolvency.

Capital:

When measuring the default risk of insurance firms, it's 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 written.

Liquidity:

In our paper, we use cash ratio to model firm's liquidity. For insurance firms, high liquidity ratio indicates good claim-paying ability. Previous studies like Carson and Scott (1997) and Bouzouita and Young (1998) show a negative correlation between liquidity risk and credit rating for insurance firms.

Gross Premium Written Growth:

Generally speaking, an increase of gross premium written[10] indicates the insurance firm is in good financial condition. Also by incorporating gross premium written into the model will automatically exclude 'run-off' firm which is very common for insurance firms from the sample (insurance firms stop writing business but may still exist for many years).

Derivative Dummy

Shiu (2011) states that insurers use derivatives to hedge risk, it may also increase their exposure of counterparty risk. In this paper, we follow the way of Shiu (2011) that label 1 for a derivative user by looking for nonzero values from Form 17 of the PRA returns.

Organizational Form

Adams (1995) argued that the organisational form can partly affect insurance firm's decision-marking. A mutual insurance firm is an organisation that supplies insurance services

[9] Difference of annual incurred claims

[10] Gross premiums written are the total premiums written which include both direct premiums written and assumed premiums written, before any reinsurance.

products, and which is owned by its customers, or members. That means there are no shareholders to pay dividends to or account to. And a mutual can concentrate entirely on delivering products and services that best meet the needs of its customers. In this paper, we separate mutual and non-mutual firm from the following pointers: firstly, mutual firms do not have share capital, and secondly another test which applies to both life and non-life is that mutual firms do not pay dividends.

Combined Raito

We add combined ratio which is (Incurred Claims + Management Expense) / Gross Premium Written) into Model to capture any mispricing problems among insurers.

Line-of-Business Concentration

Insurers with high line-of-business concentration may have higher earning risk. In this paper, We followed the method of Shiu(2011) by using Herfindahl index to proxy line-of-business concentration. first group *line of business* into model calibration, using Herfindahl Index (higher number means lower level of business mix, max number is 1):

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

Where s_i is the premium written of one business line / [Gross Premium Written (Total Primary direct & fac. Business) – Gross Premium Written (Total Treaty reinsurance accepted business)].

GDP Growth

The Annual percentage growth rate of GDP at market prices is based on constant local currency. Aggregates are based on constant 2005 U.S. dollars.

Change of Wholesale Price Index (2010=100)

Wholesale price index refers to a mix of agricultural and industrial goods at various stages of production and distribution, including import duties.

Change of Foreign Direct Investment, net inflows

Foreign direct investment refers to 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[11].

Real Interest Rate

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, limiting their comparability.

Real Effective Exchange Rate Index (2010=100)

Real effective exchange rate is the nominal effective exchange rate (a measure of the value of a currency against a weighted average of several foreign currencies) divided by a price deflator or index of costs.

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 where data are available (including corporations that do not accept transferable deposits but do incur such liabilities as time and savings deposits)[12].

3.2 Summary Statistics

Table 1

Summary Statistics - Full Sample

	Max	Min	Median	Average	Std
PT	0.31	-0.30	-0.01	-0.01	0.06
Lev	1.36	0.02	0.60	0.59	0.32
Size	17.83	1.29	11.31	11.34	2.18
CA	0.99	0.00	0.11	0.21	0.23
GPW %	11.21	-3.50	0.03	0.08	0.93
Rein	1.00	0.00	0.24	0.32	0.30

[11] According to the World Bank, ownership of 10 percent or more of the ordinary shares of voting stock is the criterion for determining the existence of a direct investment relationship.
[12] Examples of other financial corporations are finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange companies.

Table 1 Continued…					
Claim %	25.89	-6.89	0.03	0.23	1.96
Growth	6.47	-9.45	0.01	0.02	0.41
Excess %	8.74	-4.22	0.05	0.17	0.96
Combined	24.12	-1.00	0.44	1.03	2.71
InvR	0.11	-0.04	0.03	0.03	0.02
H-Index	1.00	0.00	0.76	0.71	0.28

Table1. 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.

Table 2

Summary Statistics - Default Firms

	Max	Min	Median	Average	Std
PT	0.29	-0.24	-0.02	-0.03	0.06
Lev	1.35	0.02	0.76	0.73	0.30
Size	15.25	5.82	11.46	11.33	1.66
CA	0.97	0.00	0.12	0.19	0.20
GPW %	8.03	-3.39	-0.07	-0.10	0.95
Rein	1.00	0.00	0.44	0.45	0.27
Claim %	25.07	-6.04	0.01	0.09	1.76
Growth	1.59	-1.42	-0.02	-0.01	0.28
Excess %	6.97	-3.43	0.01	0.09	1.01
Combined	24.06	-0.98	0.48	1.75	3.47
InvR	0.09	-0.03	0.02	0.02	0.02
H-Index	1.00	0.19	0.78	0.73	0.26

Table2. 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.

Table 1 shows that the standard deviation (Std) of underwriting profitability (PT) and investment return (InvR) are very small. This may indicate that the insurance industry is relatively stable[13]. Firms, on average, have higher investment profit than the traditional underwriting profit[14]. This could be due to derivative trading and other investment activities (Schinasi (2006) and Rule (2001)). On average, general insurance firms in UK hold more than 17 % (excess) capital as they have to comply with more rigorous capital requirements than financial institutions (Harrington 2009). The size of the firms change a lot during the sample period suggesting that, though the whole industry is relatively stable, yet many insurance firms transfer their business to others before they become insolvent[15]. This is also why, in this paper, we consider the transfer of the business to other companies as a possible form of exit. The high volatility of combined ratio (Combined) could be due to mispricing problem. The fluctuated incurred claim (Claim %), which requires changes in capital reserve, could capture a potential liquidity risk for insurers. The Herfindahl index is 0.71 on average with a small standard deviation. This supports the view that the insurance firms are stable and their business not very diverse.

Table 2 show that on average, comparing it to the full sample data which also includes survival and insolvent firms, default firms have negative both underwriting profitability ratio (PT), change of gross premium written (GPW %), smaller firm's size (Size), lower claim cash ratio (CA), change (Claim %), growth rate (Growth), change of excess capital (Excess %) and investment return (InvR). This indicates that default firms lose money from their main business and their investment performance is not as good as others. Also they are relatively small size firms with slow business growth. And holding less capital makes these firms more vulnerable. On the other hand, default firms have higher leverage, reinsurance ratio, combined ratio and Herfindahl index (H-index) which suggesting that they're more exposed to interest risk, credit risk and market risk. The results in the tables are in line with the current literature, for example, Adams et al. (2003) and Shiu (2011).

[13] Comparing to banks, insurers do not face 'bank run' risk and claim payments are normally takes longer time than withdrawing cash from banks.
[14] Invest in high-risk portfolios may have higher return than normal underwriting business.
[15] To protect the interests of policy-holders, Insurance firms are more likely to stop writing new business or transfer their business to other firms instead of become insolvent.

Table 3

Correlation Matrix of Firm-specific Variables

	PT	Lev	Size	CA	GPW %	Rein	Claim %	Growth	Excess %	Combined	InvR	H-Index
PT	1.00	-0.30	-0.08	0.08	0.00	-0.07	-0.07	-0.01	0.09	-0.08	-0.10	0.13
Lev	-0.30	1.00	0.46	-0.22	0.00	-0.13	-0.01	0.05	-0.01	0.05	0.01	-0.23
Size	-0.08	0.46	1.00	-0.42	-0.01	0.00	0.00	0.15	0.05	-0.08	-0.08	-0.46
CA	0.08	-0.22	-0.42	1.00	0.05	-0.16	0.01	0.01	0.03	-0.03	0.16	0.18
GPW %	0.00	0.00	-0.01	0.05	1.00	-0.05	0.23	0.32	0.02	-0.11	0.01	-0.06
Rein	-0.07	-0.13	0.00	-0.16	-0.05	1.00	0.00	-0.04	0.00	0.05	-0.33	-0.14
Claim %	-0.07	-0.01	0.00	0.01	0.23	0.00	1.00	0.18	0.02	-0.08	0.01	0.00
Growth	-0.01	0.05	0.15	0.01	0.32	-0.04	0.18	1.00	0.25	-0.17	-0.05	-0.07
Excess %	0.09	-0.01	0.05	0.03	0.02	0.00	0.02	0.25	1.00	-0.04	0.00	0.00
Combined	-0.08	0.05	-0.08	-0.03	-0.11	0.05	-0.08	-0.17	-0.04	1.00	-0.04	0.11
InvR	-0.10	0.01	-0.08	0.16	0.01	-0.33	0.01	-0.05	0.00	-0.04	1.00	-0.06
H-Index	0.13	-0.23	-0.46	0.18	-0.06	-0.14	0.00	-0.07	0.00	0.11	-0.06	1.00

Table3. 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 whole industry.

Table 3 shows the correlation matrix of the (12) firm-specific variables. Underwriting profitability (PT) is negatively correlated with leverage (Lev) and reinsurance ratio. This indicates that the financing activities through debt and reinsurance may reduce firm's profit. The firm size has a positive relationship with leverage (Lev) but a negative one with cash ratio (CA). This could indicate that large firms are relatively higher leveraged and hold less cash. Finally, firm size and the Herfindahl index (H-index) are negatively correlated, which suggest that large firms have a relatively concentrated business. We also find that firms writing more business (GPW %), normally would grow faster (i.e. have more admissible assets). Sometimes, fast growing is not a good sign of insurers, a typical example is the firm 'Independent Ins' which grew extremely fast before it suddenly busted[16].

4. Model

Default risk modelling is fast developing in recent years. Beaver (1966, 1968) and Altman (1968) first proposed scoring models which calculate firms' default probability 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 in credit scoring and structural models above. When modelling probability of default based on accounting data, the estimate of probability of default is aimed to measure an event in the future, but financial statements are designed to capture past performance of the firm. As a result, the accounting data may not have a strong prediction power about the future status of the firm. Also, Hillegeist et al., (2004) find that due 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 by market prices. However market prices may not contain all publicly available default-related information of the firm. Also the term structure, other liabilities and off-balance liabilities are not well specified in structural models when calculating default threshold of the firm, which may lead to an inaccurate estimation of default probability.

[16] Independent Insurance Company Limited ("Independent") wrote general insurance and reinsurance business mainly covering liability, property, motor and other insurance for the commercial and personal lines sectors. On 17 June 2001, the Directors of Independent presented a petition to the High Court for the winding-up of the company on the basis that Independent was insolvent and could not pay its liabilities in full. http://www.pwc.co.uk/services/business-recovery/insights/brs-uk-ins-assignments-independent-insurance-company-limited.html

As a result, in this paper we apply reduced-form models which are becoming very popular in recent years for individual firms' probability default estimation. Jarrow and Turnbull (1995) first introduced the reduced-form model which was further enhanced by Duffie and Singleton (1999). The reduced-form model assumes 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 does not directly link to the firm's assets value. This makes the models more tractable. Duffie, et al., (2007) first proposed doubly stochastic Poisson model with time-varying covariates and then forecasted the evolution of covariate process using Gaussian panel vector autoregressions. The model is further developed by Duan, et al., (2012) which applies the pseudo likelihood 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. And the doubly stochastic process approach used in this paper, considers the stochastic intensity to have a liner relationship with macroeconomic and firm-specific variables. This method has been widely applied in the literature. For example, modelling default risk by using a doubly stochastic process first presented by Duffie *et al.,* (2007), and further developed later. Duan *et al.,* (2012) provides a forward intensity model for multi-period default perdition without covariates forecasting.

The overlapped pseudo-likelihood function is used and the pseudo-likelihood function can be decomposed to different forward times.

A doubly-stochastic formulation of the point process for default is proposed by Duffie *et al.*, (2007), where the conditional probability of default within τ years is

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

X_t is the Markov state vector of firm-specific and macroeconomic covariates. λ_t (i.e. 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 like merger and acquisition or in our case firms transfer their business to other firms, the intensity is defined as φ_t. Thus the total exit intensity is $\varphi_t + \lambda_t$.

The forward default intensity censored by other forms of exit:

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

And the forward combined exit intensity is defined as:

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

4.1 Estimation

In this paper, we follow the pseudo maximum likelihood estimation method derived by Duan (2012) to estimate the forward default intensity. The details of derivations of large sample properties can be found Appendix A in Duan (2012) paper. In short, the pseudo-likelihood function for the prediction time τ defined as

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

Our sample period start from 0 to *T* measured in years. Firm *i* first appeared 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 $\tau_{Di} = \tau_{Ci}$. In other case, it will be $\tau_{Ci} < \tau_{Di}$. As we discussed in the last section, X_{it} here are the covariates which including common factors and firm-specific variables. The prediction horizon τ here is measured in years with each equal to $\Delta t = 1$. And α and β are model's parameters for default and other exit process respectively.

According to the doubly stochastic assumption or known as conditional independence assumption, firms default probabilities only depend on common factors and firm-specific variables. And firms' default probabilities are independent from each other, which indicate that one firm's default will not influence other firms' exit probabilities.

And the likelihood function $\mathcal{L}_{\tau,i,t}(\alpha, \beta)$ for firm i consists of five situations: the first is the firm i survives in the prediction time period. The second is the firm i defaults[17] in the prediction period, and the third is the firm i exits for other reasons, in our sample means the

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

insurance firm transferred their business to other firms. The fourth is the firm *i* exits after this prediction time period and the last is the firm *i* exits before the start of this time interval:

$$\mathcal{L}_{\tau,i,t}(\alpha,\beta)$$

$$= 1_{\{t_{0i}\leq t,\tau_{Ci}\geq t+\tau\}}P_t(\tau_{Ci} > t+\tau) + 1_{\{t_{0i}\leq t,\tau_{Di}= \tau_{Ci}\leq t+\tau\}}P_t(\tau_{Di} = \tau_{Ci} \leq t+\tau) + 1_{\{t_{0i}\leq t,\tau_{Di}\neq \tau_{Ci},\tau_{Ci}\leq t+\tau\}}P_t(\tau_{Di} \neq \tau_{Ci}, \tau_{Ci} \leq t+\tau) + 1_{\{t_{0i}>t\}} + 1_{\{t_{Ci}<t\}}.$$

The pseudo-likelihood function $\mathcal{L}_{\tau,i,t}(\alpha,\beta)$ can be numerically maximized to get the estimated parameters $\hat{\alpha}$ and $\widehat{\beta}$. Due to the overlapping nature of the pseudo-likelihood function above, the inference is not immediately clear. For example, at time t_5 and the prediction horizon $\tau = 2$, the firm *A* default over the this period (in this case, 2 years) that starts one period ahead (1 year ahead, t_4 to t_6) will be correlated with the firm B which default over the next time point (t_6 in this case, and the default start from t_5 to t_7) because of an overlapping common period (i.e. t_5 in our case). Duan (2012) derives the large sample properties of this pseudo-likelihood function.

In addition, this pseudo-likelihood function can be decomposed to two process α and β. And then each process can be further decomposed to different prediction horizon τ. As a result, estimates of $\hat{\alpha}$ and $\widehat{\beta}$ cam be obtained at the same time.

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

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

In order to test the consistency of the model, we split the sample by using data up to the year of 2010, 2011, 2012, 2013 and 2014. And then we calibrate the model by using the four different samples.

5. Model Outputs:

Table 4

Estimations Results

	2010	2011	2012	2013	2014
Parameters					
C	-19.364***	-25.172***	-24.116***	-25.313***	-26.959***
	(-6.143)	(-7.441)	(-7.798)	(-8.054)	(-8.411)
GDP_growth	-0.092	-0.019	-0.028	-0.010	-0.013
	(-0.062)	(-0.083)	(-0.087)	(-0.090)	(-0.098)
Real_IR	0.009	0.034	0.085**	0.098**	0.109**
	(-0.055)	(-0.045)	(-0.042)	(-0.043)	(-0.043)
Real_EXrate	-0.003	0.006	0.006	0.007	0.007
	(-0.009)	(-0.011)	(-0.012)	(-0.012)	(-0.013)
FDI %	-0.027	0.008	-0.052	-0.109	-0.073
	(-0.086)	(-0.089)	(-0.067)	(-0.075)	(-0.072)
Wholesale Price %	17.830***	23.977***	21.153***	21.988***	22.777***
	(-5.355)	(-6.754)	(-6.691)	(-6.998)	(-7.452)
Credit by Financial %	-5.103**	-6.674***	-5.011***	-4.824***	-4.323***
	(-2.001)	(-2.244)	(-1.650)	(-1.669)	(-1.586)
PT	-4.112***	-4.409***	-4.815***	-4.867***	-4.895***
	(-1.328)	(-1.143)	(-1.204)	(-1.224)	(-1.284)
Lev	1.863***	1.840***	1.966***	1.973***	1.972***
	(-0.311)	(-0.296)	(-0.311)	(-0.313)	(-0.323)
Size	0.030	0.028	0.016	0.018	0.022
	(-0.061)	(-0.059)	(-0.061)	(-0.061)	(-0.062)

Table 4 Continued…

CA	-0.182	-0.160	-0.228	-0.224	-0.210
	(-0.574)	(-0.549)	(-0.560)	(-0.561)	(-0.562)
GPW%	-0.180	-0.435***	-0.416***	-0.413***	-0.414***
	(-0.175)	(-0.109)	(-0.108)	(-0.109)	(-0.111)
Rein	1.109***	1.003***	1.091***	1.108***	1.123***
	(-0.275)	(-0.259)	(-0.270)	(-0.279)	(-0.304)
Claim%	0.041***	0.040***	0.055***	0.053***	0.052***
	(-0.015)	(-0.015)	(-0.015)	(-0.015)	(-0.015)
Growth	0.014	-0.010	0.055	0.060	0.059
	(-0.120)	(-0.105)	(-0.115)	(-0.116)	(-0.118)
Eecess%	-0.287**	-0.281**	-0.230*	-0.231*	-0.229*
	(-0.122)	(-0.113)	(-0.122)	(-0.123)	(-0.123)
InvR	-25.362***	-25.449***	-25.184***	-24.899***	-24.849***
	(-5.517)	(-4.585)	(-5.832)	(-6.190)	(-7.364)
Combined Ratio	0.024***	0.023**	0.025**	0.025**	0.026***
	(-0.009)	(-0.010)	(-0.010)	(-0.010)	(-0.010)
Herfindahl index	0.606	0.508	0.439	0.435	0.429
	(-0.380)	(-0.367)	(-0.373)	(-0.374)	(-0.377)
Derivative Dummy	0.607**	0.641**	0.655**	0.653**	0.654**
	(-0.278)	(-0.281)	(-0.276)	(-0.275)	(-0.275)
Organizational Form	0.509	0.528*	0.553*	0.559*	0.642**
	(-0.321)	(-0.316)	(-0.308)	(-0.310)	(-0.303)

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

Table4. 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 organizational form based on five different samples using data from 1985 to 2010, 2011, 2012, 2013 and 2014 respectively. Results of multi-periods (5 years horizon) estimation which based on full sample (1985-2014) can be found in Appendix B and Appendix C.

Table 4 shows we have the results for the sample periods 1985 to 2010, 2011, 2012, 2013 and 2014 respectively. We split the whole sample (1985 to 2014) into five subsamples to see if a variable is consistently significant.

Overall, most our results are in line with Adam et al., (2003). Leverage, profit, reinsurance and organizational form[18] are significant factors both in assessing the credit risk of insurance firms and determining the quality of credit rating. On the other hand, firm size and growth are not significant[19]. New risk factors are found in both macroeconomic and firm-specific variables, like the change of credit provided by financial institutions, whole sale price change, investment profitability, combined ratio, and the usage of financial derivatives.

Across the different samples, whole sale price change, credit provided by financial institutions change, underwriting profitability, leverage, reinsurance, change of incurred claims, excess capital, investment profitability, combined ratio and the derivative dummy, are always significant. In general, GDP growth, real interest rate and the change of whole sale price have a positive effect of default intensity. This could indicate higher default probability (PD). On the other hand, if more credit is provided by the financial sector, this will lower firms' PD. Writing Profitability and investment profitability are negatively correlated with the default intensity. This could indicate that high profitable firms will be less likely to become insolvent. Our results are consistent with Titman and Wessels (1988) and Frank and Goyal (2009). Our results are also consistent with Carson and Scott (1997) and Bouzouita and Young (1998), which show that higher liquidity is consistent with higher credit rating. Our results show that firms holding more capital, generally, have higher liquidity and lower default probability. In general large firms typically have a good reputation and therefore it's easier for them to get credit in the market. Also Bouzouita and Young (1998) find large

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

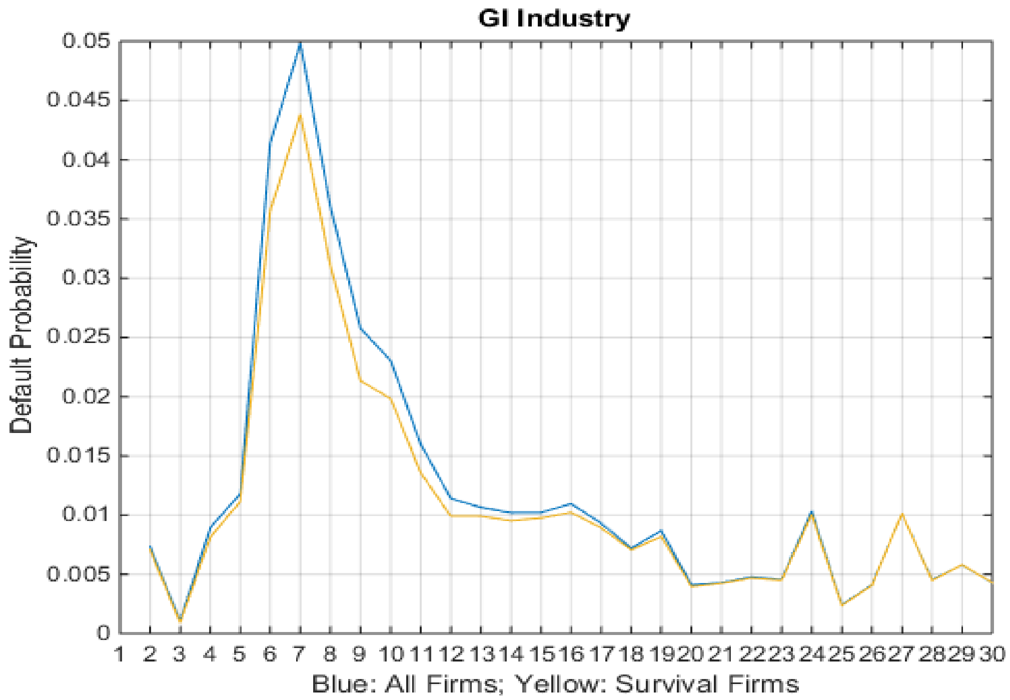
[19] This could be due to the difference in the dataset. In our paper, we have 363 general insurance firms and data from 1985 to 2014. Adam et al., (2003) paper instead, use only 40 firms rated by A.M. Best plus 25 firms rated by S&P and they apply both general insurance and life insurance firms into the model.

insurers are less likely to default, but our results suggest firm size is not significant in determining the solvency of insurance firms. Firms with larger gross premium written will not only bring cash inflow in the short term but also potential claims in the long term. The one-year PD estimation results show that writing more premiums will lower insurer's default probability.

On the other hand, highly leveraged firms are less likely to survive during depressed times and as a result they normally have a higher PD. Ad-hock structured reinsurance may reduce the credit risk exposure, and the findings from Adams (1996) show that reinsurance improve the ability of the primary insurer to survival an external economic shock. But our results show the positive relationship between reinsurance and PD which suggesting that heavily reinsured firms are more likely to default. Our results also indicate the effect of negative perspective of reinsurance's counter party cannot be ignored.

One important question is if using derivatives increases the counterparty risk or if it is only useful for hedging. For example, derivatives could be used for hedging risk, but Shiu (2011) shows that it could also increase the exposure to counterparty risk. Our results suggest that the use of derivatives may increase the probability of a firm becoming insolvent.

5.1 Overall Default Probability (bps)



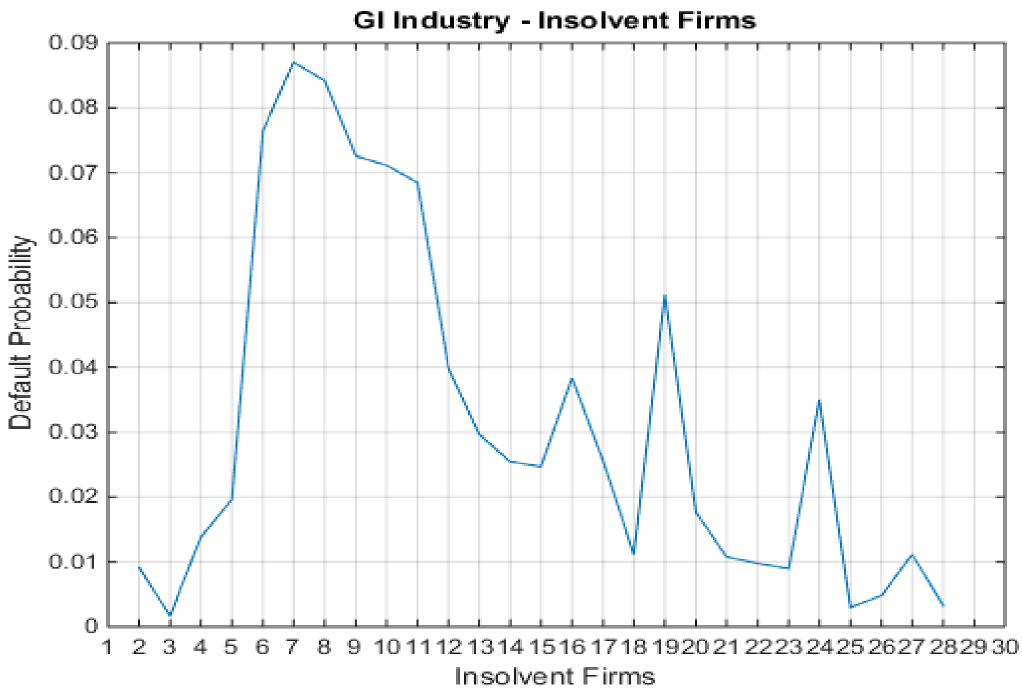


Figure1. PD of all firms and insolvent firms. One-year default probability of GI firms from 1986 to 2014. Different samples based on data from 1985 to 2010, 2011, 2012, 2013 and 2014.

Figure1 shows that the PD of insolvent firms is much higher and fluctuates more compared to the performance of the whole GI industry. The highest PD of insolvent firms is about 0.09 which is almost double that of the whole industry. For the GI industry, the PD peaks around early 90s and successively decreasing until 2000. The PD is relatively low but became more volatile before the financial crisis with a sharp increase in 2008 when the global financial crisis happened. The PD of insolvent firms peaks around 1990 and decreasing until 1998. Two big increases appear in 2000 and 2003, before the 2008 global financial crisis. The average PD for default firms is 317 bps and 124 bps for the whole industry (112 bps for survival firms). The standard deviation for default firms is 0.0276 that is much higher than the whole industry level (0.0119) and the survival firms (0.0101). In general, default firms are more risky compared to the whole GI industry.

5.2 Default Probability and Spread Between Default and Survival Firms

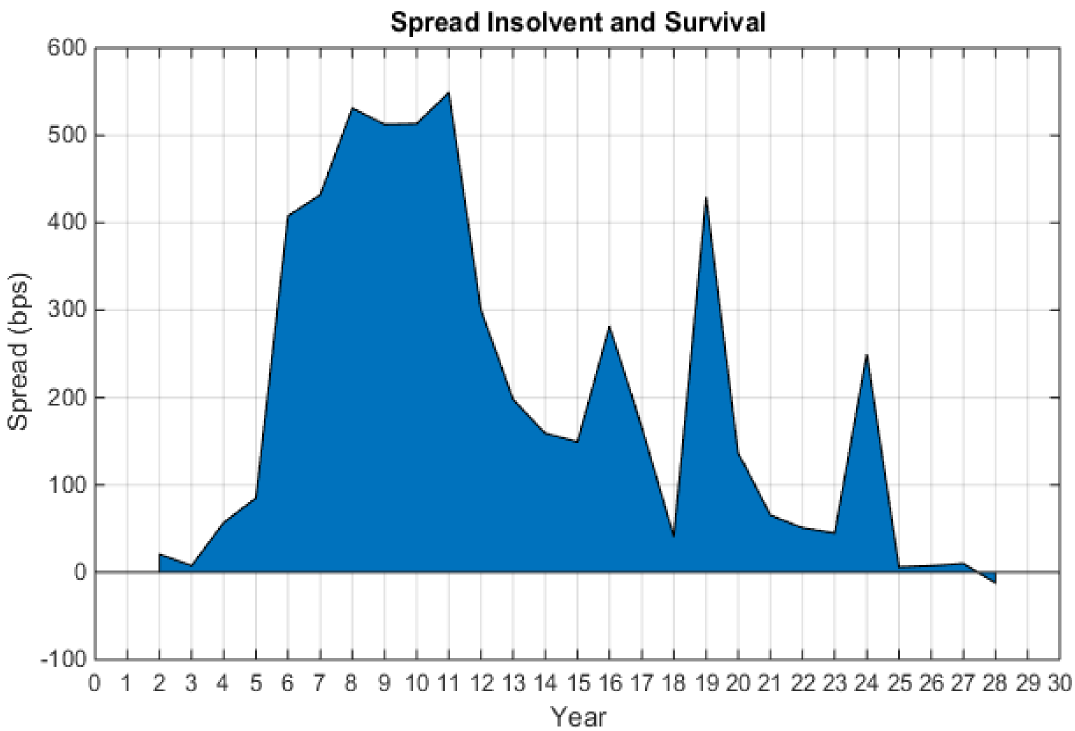
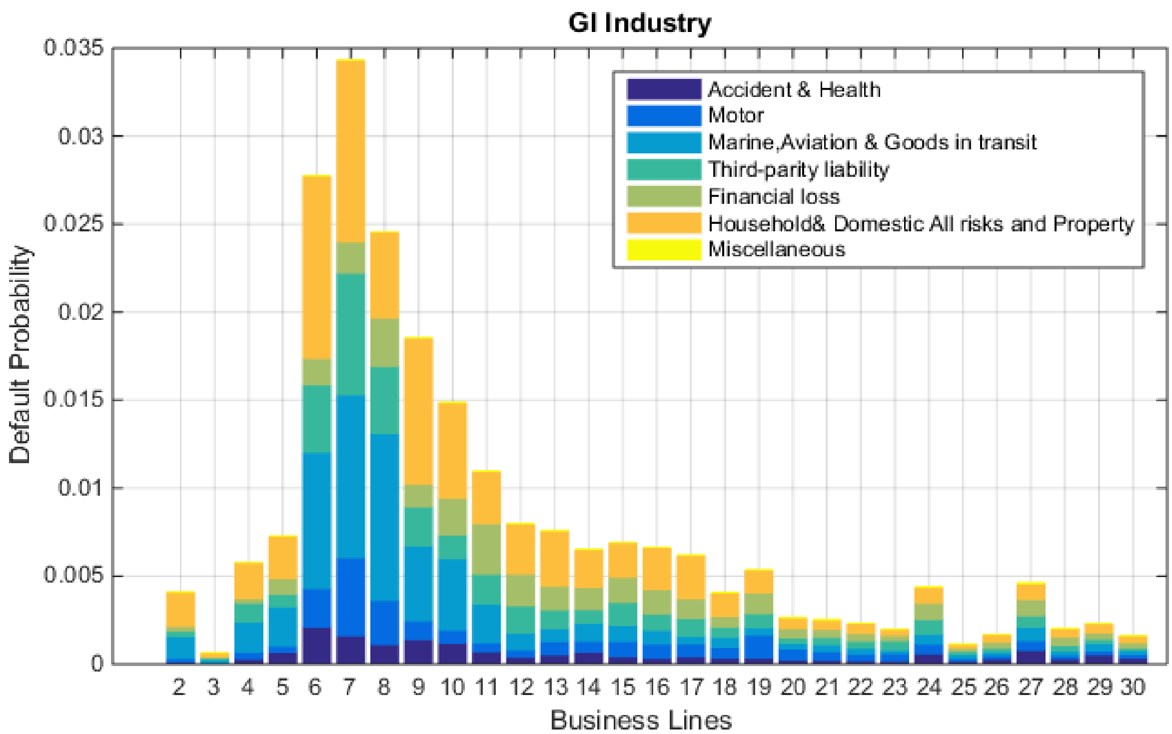


Figure 2. PD of Survival firms and spread between default and survival firms. One-year default probability of survival firms and the spread between survival and default firms from 1986 to 2014.

Figure 2 shows a large PD spread between insolvent firms and the whole GI industry during early 90s and a quick increase of the PD spread around the year of 2000, 2003. Generally, a positive credit spread is found before the year of 2009. During the financial crisis, the spread is increasing rapidly compared to before, which indicates that all insolvent firms face a worse financial situation and are more vulnerable than the whole GI industry. After the 2008 financial crisis, the spread is much smaller or even negative.

6. PD in Different Business Lines

Generally insurance firms have business in different sectors and firms may change their main business line through the time. Apart from the business concentration, the change in the credit risk in different sectors has also important implication for the regulators' supervision and policy-making decisions. Based on the gross premium written of different business lines of each firm, we classify the insurance firms into 7 Groups in accordance to their main business lines: 1. Accident & Health; 2. Motor; 3. Marine, Aviation & Goods in transit; 4. Third-parity liability; 5. Financial loss; 6. Household& Domestic All risks and Property; 7.Miscellaneous.



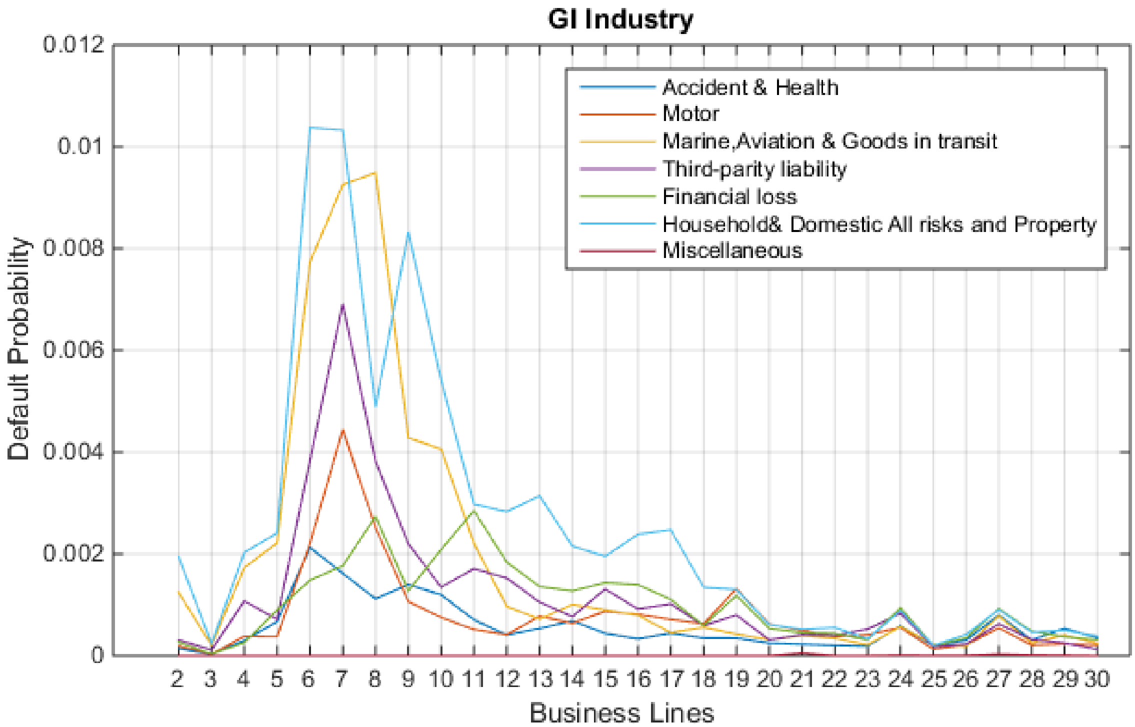


Figure 3. PD of 7 Groups. One-year default probability 7 groups which contain PD from 1986 to 2014.

Before 1995, household & domestic all risk and property (group6) has the highest default probability with marine, aviation & goods in transit (group3) being the second. The third-party liability (group5) is the third and accident & health (group1) is the last one. After 1995, the PD of group6 and group3 is decreasing while that of group5 and group1 are fluctuating around their average. All groups show an upward trend of their PDs during the financial crisis.

During the 2008 global financial crisis, the PD of all groups except marine, aviation & goods in transit and miscellaneous, which are relatively flat, are increasing. After the financial crisis, the financial loss group and household & domestic all risk & property become the most risky groups.

7. Default Clustering-System Risk

After obtaining the individual PD, it's natural to look at the system risk within insurance industry. Here we calculate pair correlations of firms among different quantiles, and use the average value to represent the default correlation. It's not surprising to find the default correlations within firms. Previews studies like Das *et al.*, (2007) find strong default correlations among corporate obligors. It's interesting to see whether the insurance firms are likely to default jointly when firms' individual PDs are high. Also, high PD correlations may suggest insurers are exposed to common factors besides firm-specific factors.

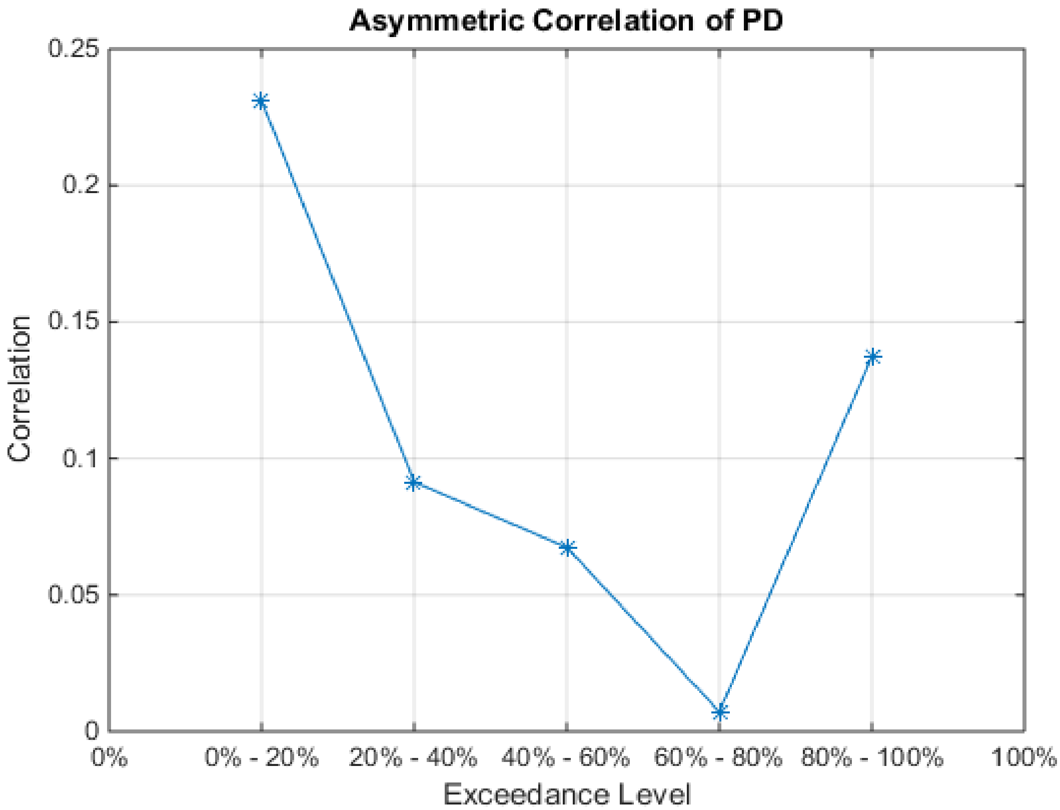


Figure 4. Asymmetric Correlation of PDs. Correlation of PDs for the different PD quantiles in our study. First rank the PD of the whole GI industry (average PD of all firms at the year) from the lowest to highest. Then we find exceedance levels according the GI industry PD. The lowest quantile 0%-20% indicates the least risky years and the highest 80%-100% quantile mean the most risky years of GI industry. And then we calculate average correlations of each pairs in the same group.

Figure 4 shows the average pair PD correlations of all firms within different groups (from low risky 0%-20% to high risky 80%-100%) based on the data from the year of 1985 to 2014. The highest PD correlations at the 0%-20% quantile and the second highest correlations found in the most risky group 80%-100%.

The new finding from figure4 is the highest correlation is among insurers with lowest PD. It suggests that when insurance firms stay in relatively safe condition, they are more likely to be exposed to some common factors, in our case, macroeconomic variables like credit supply and whole sale price change. At most times, when insurers are more risky, the PD correlation becomes lower. At this stage, the credit risk insurance firms are more affected by firm-specific variables. But insurers within the highest 80%-100% quantile have the second highest PD correlation which indicating that their credit risk are affected by both common factors and firm-specific factors. The trend of PD correlations among different quantiles supports our previous variables choice that taking both macroeconomic and firm-specific factors into considerations. Overall, our empirical results are in line with Bell and Keller (2009) that insurers are less interconnected than banks and there is a lower contagion effect among insurers. The average PD correlation across firms is 0.1069. The PDs within lower 20% quantile has the highest correlation of 0.2311. We find the lowest correlation is 0.0072. While the PD correlation of the group '40% - 60%' is much higher which is 0.0675. And the PD correlation of group '20% - 40%' is slightly higher than the group '40%-60%' which is 0.0914. The '80%-100%' group shows the second largest PD correlation that is 0.1375. The highest PD correlation is found in the group '0%-20%' indicates that during safe time, most insurance firms are staying in a good financial condition together. And the second highest PD correlation which not deviates from the average value a lot in the group ''80%-100% suggests that there is a slightly default clustering in the insurance industry.

8. Reinsurance and Default Risk

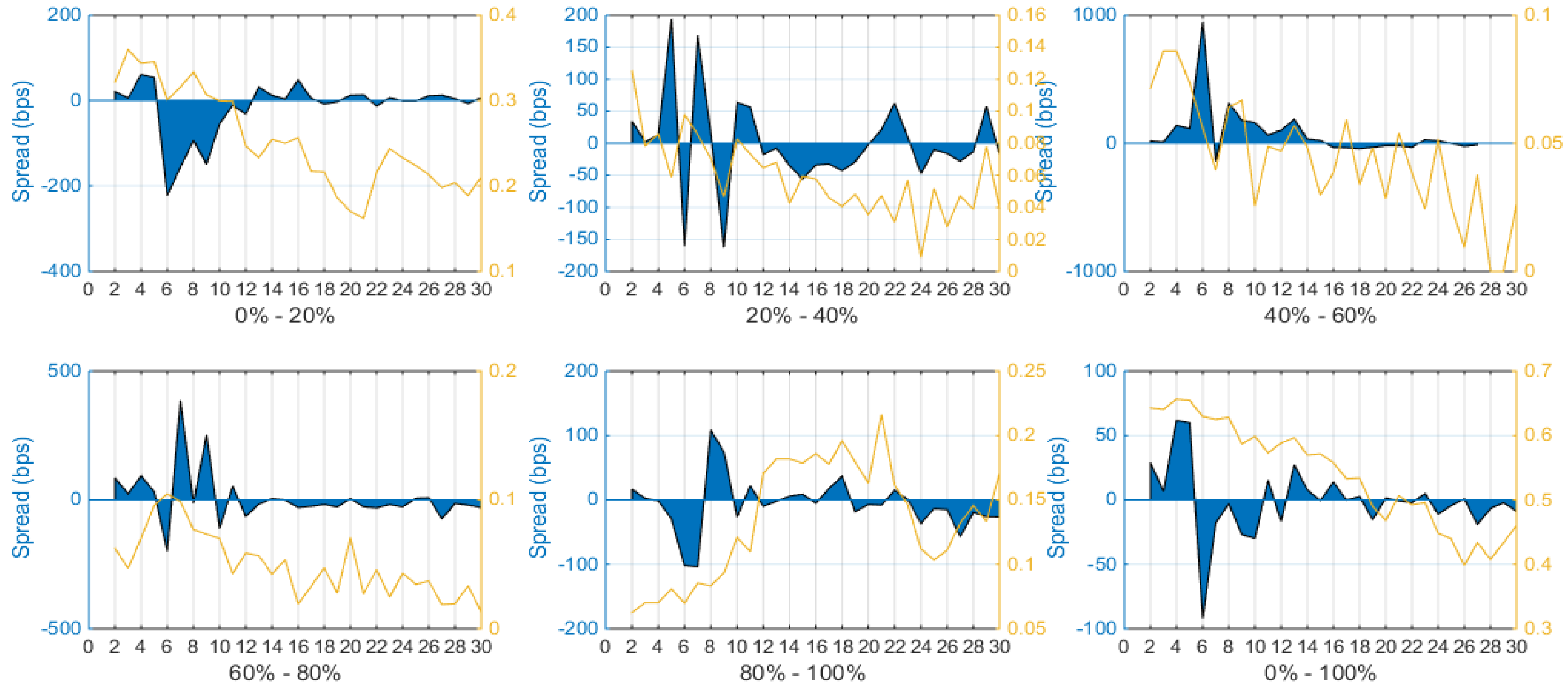


Figure 5. Credit spread when taking Reinsurance. Credit spread between firms accepting reinsurance and firms not accepting reinsurance at different levels (full sample calibration). Orange line: percentage of firms with reinsurance accepted at certain level; blue line: credit spread.

Previous researches show that corporate hedging decisions like reinsurance affect the strategic performance of firms (Harris and Raviv, 1991; Adam et al., 2007). Reinsurance is a pure hedging contract that enables primary insurers to transfer risks to third parties. Harrington and Niehaus (2003) suggest that reinsurance is important because of solvency risk matters to both policyholders and regulators.

Under the *Solvency II*, the technical provisions are calculated gross, with reinsurance calculated separately. The counter-party risk of reinsurance cannot be ignored and as a result, the technical provision of reinsurance is incorporated under the *Solvency II*. In this section, we investigate the performance of the firms when these are assuming reinsurance at different levels. We first classify firms into different groups based on the percentage of reinsurance they accept in relation to their total written gross premium and then we study the credit spread of firms who accepted reinsurance across the different groups. As Aunon-Nerin and Ehling (2008) study shows that indemnity contracts like reinsurance contracts are pure hedging instruments. Adam and Upreti (2015) find that reinsurance enables primary insurers to have sufficient risk capacity for planning and pricing new business lines. Therefore, the insurers may be exposed to new risks through risk financing. And reinsurers (i.e. firms accept reinsurance) exposed to claims volatility and potential loss events, but in return receive a share of annual premiums written.

The maximum spreads for each group are 61 bps, 194 bps, 945 bps, 386 bps, 109 bps, and 62 bps respectively. The standard deviations are 0.0064, 0.0073, 0.0198, 0.0104, 0.0042 and 0.0027 respectively. For each group, we calculate the credit spread between firms accepting reinsurance and firms not accepting reinsurance.

From Figure 5, in general, the lower 20% firms have negative spread especially during the early 90s to the firms without accepting reinsurance. This may indicate that firms being less involved into the reinsurance market often have good creditworthiness and take reinsurances being, most likely, part of the firm's business plan[20]. Unlike the firms with less 20% reinsurance, firms which accept 20% to 40% reinsurance are more uncertain about having positive or negative spread. They have both large negative and positive spread through the sample period. For these firms, during the financial crisis, compared to firms which do not accept reinsurance, the spread is negative. For the group of firms which accept between 40%

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

to 60% and 60% to 80% reinsurance, the spread is negative most of the time except the big positive spread during 90s[21]. Finally, the group accepting more than 80% reinsurance has positive and negative spread at most of the time before financial crisis. And the spread peaked during the early 90s[22]. However, after financial crisis, the spread becomes relative small and sometimes negative.

In terms of firm size, the percentage of firms for each group is changing over years. The total percentage of firms accepting reinsurance peaked in 1988 and decreases afterwards. Most firms accept less than 20% reinsurance, and the percentage of firms is decreasing since the year of 1987. Less than 50% firms accept 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 and the number of firm peaked in 2005.

Overall, the average spread between firms accepting reinsurance and firms without any reinsurance accepted is only -1 bps, which indicates a slightly smaller credit risk. In our 29 years sample, the results show that 12 years with positive spread 17 years with negative spread. And surprisingly the results show that overall firms accepting reinsurance have lower default probability especially during bad times (i.e. early 90s Burns' Day Storm and 2008 financial crisis). This is a new and important result. Doherty and Tinic (1981) find that reinsurance contracts make primary insurers to manage cash flow volatility more effectively, have better future underwriting capacity, and decrease the insolvency probability. Our results show that, on the other hand, reinsurers benefit from these indemnity contracts by proper risk management that reinsurance enables reinsurers to reduce their default probabilities.

9. Concluding Remarks

This paper analyse the credit risk of general insurance (GI) firms in the UK using data from 1985 to 2014. We firstly apply reduced form model to access the credit risk of GI firms by considering both insolvency and other exit like transferring business into consideration. Our results show that most classic risk factors (for example, profitability, leverage and reinsurance etc.) are significant for assessing insurers' credit risk. In addition, we find insurance firms are exposed to some common factors and new firm-specific risk factors like usage of financial derivatives and investment profitability are found. Overall, macroeconomic

[21] The Burns' Day Storm occurred on 25–26 January 1990 over north-western Europe and is one of the strongest European windstorms on record. Winds of up to 100 mph kill 97 people and cause £3.37 billion worth of damage, the most costly weather event for insurers in British history.
[22] Affect by the Burns' Day Storm occurred in 1990.

factors (GDP growth, interest rate, whole sale price and credit provided by financial institutions) and firm-specific factors (underwriting profit, leverage, growth premium written, reinsurance, incurred claims, excess capital, combined ratio, investment profit, usage of derivatives and organizational form) are significant in assessing the credit risk of general insurance firms.

After exploring the sources causing insolvency, we further analyse the credit risk of firms with different main business line. It appears that in the early 90s, due to natural disasters at that time, household & domestic all risk has the highest credit risk and after financial crisis, third-party liability become the most risky sector. The time-varying PD could provide regulators warning signs of the risky sector and it could also benefit the regulators' policy-making decisions like temporally increasing their minimum capital requirement or more closely supervision on specific firms.

Also we find overall, the default correlation between different insurance firms are low, but there is a slightly default clustering in the GI firms. The default correlations among insurers suggest insurance firms may be exposed to common risk factors. At last we study the relationship between how much reinsurance assumed and credit risk of GI firms. The empirical results suggest that different levels of reinsurance assumed highly affect the credit risk of the insurance firms themselves. Our empirical results suggest that reinsurers could also benefit from reinsurance contracts that have a lower default probability comparing to insurers even at distressed times. This may provide implications to regulators of the GI firms' supervision under the coming Solvency II which newly incorporating reinsurance into technical provision calculations.

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Appendix A - Insolvency cases:

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

Appendix B - Multi-period Default Estimation Outputs

	1	**2**	**3**	**4**	**5**
C	-26.959***	-37.507	-36.182	-49.547	-18.585
	-8.411	-125.922	-61.624	-110.445	-93.697
GDP_growth	-0.013	0.045	0.079	0.449	0.015
	-0.098	-0.870	-0.373	-0.694	-0.432
Real_IR	0.109**	0.217	0.152	0.265	0.189
	-0.043	-0.422	-0.322	-0.770	-0.598
Real_EXrate	0.007	0.011	0.004	0.019	-0.003
	-0.013	-0.275	-0.145	-0.238	-0.220
FDI %	-0.073	0.022	-0.148	-0.095	-0.022
	-0.072	-0.865	-0.546	-0.566	-0.183
Wholesale Price %	22.777***	25.717	24.151	38.491	6.943
	-7.452	-95.525	-49.076	-88.161	-77.494
Credit by Financial %	-4.323***	-0.286	0.584	-2.292	4.415***

	-1.586	-1.295	-0.878	-1.739	-0.801
PT	-4.895***	-3.455	1.090	1.096	3.884
	-1.284	-38.286	-34.568	-53.766	-66.484
Lev	1.972***	2.134	1.857	1.585	2.288
	-0.323	-5.682	-4.868	-7.259	-9.352
Size	0.022	0.127	0.120	0.062	-0.146
	-0.062	-0.607	-0.310	-0.410	-0.472
CA	-0.210	0.210	-0.001	-2.414	-2.698
	-0.562	-0.757	-1.692	-5.414	-1.921
GPW%	-0.414***	-0.143	0.098	-0.164	0.016
	-0.111	-0.506	-0.280	-0.456	-0.432
Rein	1.123***	1.898	2.034	1.783	1.078
	-0.304	-9.542	-6.758	-9.141	-8.315
Claim%	0.052***	-0.012	-0.003	0.040	0.047
	-0.015	-0.331	-0.079	-0.217	-0.164
Growth	0.059	0.111	0.283	0.187	0.251
	-0.118	-1.817	-1.759	-2.643	-2.181
Eecess%	-0.229*	-0.261	-0.187	0.027	-0.101
	-0.123	-0.671	-0.356	-0.471	-0.598
InvR	-24.849***	-14.780	-4.048	-9.868	-3.836
	-7.364	-301.181	-205.288	-303.345	-303.642
Combined Ratio	0.026***	0.013	0.025	0.017	0.065
	-0.010	-0.092	-0.036	-0.148	-0.049
Herfindahl index	0.429	1.021	1.683*	1.994	1.512
	-0.377	-2.248	-0.978	-2.022	-1.518

Derivative Dummy	0.654**	0.298	0.521	0.528	0.967
	-0.275	-0.757	-0.390	-0.359	-0.779
Organizational Form	0.642**	0.604	0.577	0.225	0.070
	-0.303	-2.535	-1.484	-1.723	-1.926

Appendix C - Multi-period Other Exit Estimation Outputs

	1	**2**	**3**	**4**	**5**
C	-2.250	-5.996	-3.812	-10.554	-6.543
	-29.285	-29.742	-18.084	-22.116	-29.397
GDP_growth	-0.046	-0.017	0.010	0.073	0.046
	-0.093	-0.045	-0.053	-0.054	-0.074
Real_IR	-0.010	0.049	0.048	0.011	-0.024
	-0.242	-0.261	-0.170	-0.216	-0.295
Real_EXrate	0.014	0.005	0.002	0.003	0.009
	-0.061	-0.058	-0.032	-0.039	-0.048
FDI %	0.002	0.011	-0.053	-0.191	0.006
	-0.132	-0.092	-0.109	-0.220	-0.092
Wholesale Price %	-4.248	-0.067	-2.454	5.550	3.514
	-23.218	-23.994	-14.397	-17.451	-26.661
Credit by Financial %	-0.535	-1.482	-1.109	-3.343	-6.793***
	-1.131	-1.070	-1.495	-2.921	-2.103
PT	-2.119	-0.118	-1.599	-2.416	-2.672
	-14.920	-16.619	-10.447	-14.400	-15.724

Lev	0.456	0.410	0.126	-0.095	-0.697
	-2.591	-2.863	-1.830	-2.345	-2.580
Size	-0.002	0.090	0.154	0.246	0.343
	-0.272	-0.288	-0.182	-0.216	-0.225
CA	-1.479*	-1.214**	-0.859**	-0.372	-0.953*
	-0.769	-0.521	-0.372	-0.414	-0.566
GPW%	-0.029	0.000	-0.018	0.035	0.038
	-0.158	-0.180	-0.122	-0.157	-0.154
Rein	0.560	0.718	0.655	0.622	0.744
	-2.674	-3.045	-2.040	-2.925	-4.098
Claim%	0.056	0.063***	0.043***	-0.088***	-0.114**
	-0.037	-0.022	-0.010	-0.030	-0.047
Growth	-0.315	-0.401	-0.447	-0.483	-0.505
	-0.756	-0.887	-0.602	-0.846	-1.132
Eecess%	-0.080	-0.014	-0.035	-0.055	-0.070
	-0.141	-0.158	-0.120	-0.191	-0.192
InvR	7.119	5.560	2.541	-0.625	7.667
	-120.960	-126.475	-82.100	-112.554	-134.414
Combined Ratio	0.097***	0.096***	0.101***	0.104***	0.043***
	-0.009	-0.010	-0.009	-0.006	-0.008
Herfindahl index	1.078**	1.496***	1.237***	1.227***	1.342***
	-0.435	-0.286	-0.253	-0.357	-0.271
Derivative Dummy	1.059**	0.636	0.349	0.316	0.454
	-0.530	-0.533	-0.327	-0.426	-0.489

Organizational Form	-0.100	-0.173	-0.131	-0.031	-0.181
	-1.230	-1.150	-0.725	-0.937	-1.021