Natural Disasters, Political Risk and Insurance Market Development

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We examine the relationship between natural disasters, political risk and insurance market development in a panel of 39 countries over the period 1984-2009 using a dynamic panel two-step system generalised method of moments model. We provide evidence that the incidences of natural disasters and deaths caused by natural disasters lead to greater total insurance, as well as life insurance and non-life insurance consumption. We also find that countries with lower levels of political risk experience higher insurance consumption. The incidences of natural disasters and deaths attributable to natural disasters contribute to insurance market development under the tenure of a government with lower levels of political risk. We therefore emphasise that natural disasters, political risk and their interaction effects are important determinants of insurance market development. The Geneva Papers (2013) 38, 406-448. doi:10.1057/gpp.2013.14

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Introduction

A considerable amount of literature has been devoted to understanding the consequences of natural disasters. This is because natural disasters have caused substantial economic damages, and, more importantly, these economic costs following a natural disaster have been significantly increasing in the past several decades. For example, worldwide economic costs from natural disasters were approximately US\$53.6 billion in the 1950s, whereas these economic damages reached roughly US\$778.3 billion by the 1990s.^{1,2} Furthermore, natural disasters caused about US\$370 billion in economic costs in 2011 alone.³ As such, natural disasters contribute to vital consequences for the local economy.

Given that natural disasters have caused significant worldwide economic damages, the 1992 United Nations Framework Convention on Climate Change has emphasised

¹ Kunreuther (2008); Michel-Kerjan and Kousky (2010).

 $^{^{2}}$ Schwarze and Wagner (2004) also provide a detailed analysis on the economic costs following natural disasters by each decade, from the 1950s to the end of 1990s.

³ Swiss Reinsurance Company (2012).

the important role of insurance industries in disaster assistance in local economies.⁴ More recently, the 2005 Hyogo Framework for Action highlights the urgency to advance the expansion of insurance markets to finance risk following a natural disaster.⁴ Cummins and Mahul⁴ argue that insurance market development is particularly important, because governments frequently redirect finances and resources from development projects for recovery efforts following a natural disaster. The political environment of a country may also considerably influence insurance market development across countries.

Hence, the primary purpose of this paper is to investigate the relationship between natural disasters, political risk and insurance consumption across countries. First, we ask, do natural disasters contribute to insurance market development? More specifically, we examine whether the incidences of natural disasters impact insurance consumption. We also assess whether deaths caused by natural disasters influence the demand for insurance. Since natural disasters cause significant economic and human losses in a local economy, households may invest in appropriate protective measures (i.e. purchase insurance policies) to acquire financial security. For example, Kunreuther⁵ indicates that "the occurrence of a disaster causing damage to one's home is likely to have a significant impact on the demand for insurance" (p. 176).

Second, we investigate whether the development of insurance markets varies under the tenure of a government with different levels of political risks. The literature providing evidence that the quality of the political environment is an important determinant of insurance market development across countries has grown significantly.⁶ Moreover, Hussels *et al.*⁷ argue that the "functioning of a working legal system and the protection it may afford policyholders is a major determinant of insurance market development" (p. 264). Thus, higher levels of political risk in a country may possibly impact the investment activities of international companies, because it raises the risk premium of an investment venture.^{8,9} It is therefore possible that countries with higher levels of political risk experience lower insurance consumption.

Third, we analyse whether the occurrences of natural disasters, and deaths caused by natural disasters, influence insurance market development under the tenure of a government with different levels of political risk. In particular, we estimate the interaction effects of natural disaster variables and political risk on insurance consumption across countries. Our argument follows Oh and Reuveny,¹⁰ who indicate that "disasters may increase political risk, and political risk may indicate how well the economy can respond to disasters and recover" (p. 244).¹¹ Since natural disasters and political risk may potentially influence each other,¹⁰ we also argue that natural

⁴ Cummins and Mahul (2009).

⁵ Kunreuther (1996).

⁶ Ward and Zurbruegg (2002); Esho et al. (2004); Feyen et al. (2011).

⁷ Hussels *et al.* (2005).

⁸ Busse and Hefeker (2007).

⁹ For example, Busse and Hefeker (2007) find that the level of political risk in a country significantly influences the inflows of foreign direct investment.

¹⁰ Oh and Reuveny (2010).

¹¹ Oh and Reuveny (2010) investigate the interaction effects of natural disasters and political risk on international trade.

disasters and political risk may possibly interact in impacting insurance market development across countries.

Finally, we examine the determinants of insurance market development using panel data for 39 countries. The analysis is based upon data recorded annually over the period of 1984–2009.¹² To account for possible heterogeneity in the dependent variable, we distinguish between life insurance and non-life insurance consumption in the empirical analysis. Hence, we use life insurance premiums, non-life insurance premiums and total insurance premiums as a percentage of gross domestic product (GDP) (insurance penetration) and (log) per capita, in constant US\$ (insurance density) to represent insurance market development. In the interest of robustness, we use five measures of natural disasters in the empirical analysis, namely, floods, earthquakes, windstorms, epidemics and climatological disasters.

We employ a dynamic panel two-step system generalised method of moments (GMM) estimator developed by Arellano and Bond,¹³ Arellano and Bover,¹⁴ and Blundell and Bond,¹⁵ who proposed a methodology to generate consistent, efficient and robust estimators in a dynamic panel data model.¹⁶ The dynamic panel GMM methodology "exploits the time-series variation in the data, accounts for unobserved country-specific effects, allows for the inclusion of lagged dependent variables as regressors, and controls for endogeneity of all the explanatory variables"¹⁷(p. 264). We employ panel data analysis to account for the presence of heterogeneity in the estimated parameters and dynamics across countries.¹⁸

To anticipate our results, we find that natural disasters are important determinants of insurance market development. More specifically, we find that the occurrences of natural disasters and deaths caused by natural disasters contribute to higher total insurance, as well as life insurance and non-life insurance consumption. We also provide evidence that countries with lower levels of political risk are associated with insurance market development. Furthermore, the incidences of natural disasters and deaths attributable to natural disasters lead to higher insurance consumption under the tenure of a government with lower levels of political risk. In effect, these results imply that a rise in the political risk level of a country mitigates the beneficial effect of natural disaster variables on insurance market development.

Overall, we provide evidence that the incidences of natural disasters and death caused by natural disasters persuade individuals to invest in necessary protective measures, that is, purchase insurance products. However, we discover that not all occurrences of natural disasters and natural disaster deaths stimulate the demand for

¹² We collect annual data for a panel of 39 countries over the period 1984–2009 in the empirical analysis primarily on the basis of data availability.

¹³ Arellano and Bond (1991).

¹⁴ Arellano and Bover (1995).

¹⁵ Blundell and Bond (1998).

¹⁶ We conduct a number of specification tests in a dynamic panel two-step system GMM model, including the Hansen and Arellano-Bond tests, to ensure that the econometric model produces consistent, efficient and robust estimates.

¹⁷ Beck et al. (2000).

¹⁸ Baltagi (1995).

life insurance and non-life insurance policies. Since floods, earthquakes, windstorms, epidemics and climatological disasters are associated with different scales of economic and human losses, it is perhaps not surprising that not all natural disasters induce residents to purchase insurance products to secure financial protection. In summary, our results provide evidence that natural disasters, political risk and their interaction effects are fundamental determinants of insurance consumption across countries.

The remainder of the paper is structured as follows. In the next section, we provide a general background on natural disasters and insurance market development. The section after that describes the determinants of insurance market development in accordance with the previous literature. Then, the definitions and data sources of all the variables used in the empirical analysis are provided. In the subsequent section, we detail the econometric model employed in the estimation. The penultimate section presents the empirical results for the baseline and the extended specifications, while the final section summarises the major findings.

General background

The literature documents that natural disasters have substantial implications for economic and political stability. This is perhaps not surprising given that natural disasters are significantly associated with a destruction of physical and human capital in a country.¹⁹ For example, natural disasters destroy water pipelines, harvests, animal life, housing, transportation and communication networks, trade, and energy transit routes in a domestic economy.²⁰

Furthermore, the empirical work of Noy²¹ investigates the macroeconomic implications of natural disasters and finds that natural disasters adversely affect a country's domestic production. In addition, Oh and Reuveny¹⁰ show that natural disasters negatively impact international trade and, therefore, emphasise that these severe natural occurrences may contribute to a slowdown in economic globalisation across nations. More recently, Strobl²² examines the macroeconomic consequences of natural disasters in developing economies and discovers that natural disasters significantly reduce economic growth.²³ As a result, natural disasters considerably deteriorate the welfare of society.

According to Hussels *et al.*,⁷ the key role of insurance markets is to finance risks by providing "individuals and businesses with coverage against specified contingencies, by redistributing losses among the pool of policyholders" (p. 259). Since natural disasters cause significant economic and human losses, insurance companies may

¹⁹ See, for example, Noy (2009); Noy and Vu (2010); Oh and Reuveny (2010); Strobl (2012).

²⁰ See, for example, Ember and Ember (1992); Miguel *et al.* (2004); Bhavnani (2006); Brancati (2007); Noy (2009); Oh and Reuveny (2010).

²¹ Noy (2009).

²² Strobl (2012).

²³ It is important to note that these natural disaster losses differ greatly across governments. For example, Kahn (2005) finds that countries with higher income, democratic institutions and stronger governments experience fewer natural disaster deaths. Also, Toya and Skidmore (2007) find that nations with higher measures of development suffer less natural disaster losses.

supply coverage against these unforeseen events. Hence, it is critically important for households and businesses to obtain insurance in order to mitigate natural disaster losses.²⁴ Athavale and Avila²⁵ explain that individuals may sustain significant monetary loses if they select not to insure against these unexpected shocks.

Thus, it is likely that individuals and businesses purchase insurance to acquire financial security, since natural disasters cause substantial economic costs in a country.²⁶ Kunreuther⁵ therefore argues that the incidence of natural disasters may considerably influence the demand for insurance in a local economy. Furthermore, Arnold²⁷ emphasises that insurance industries "form a critical part of a comprehensive disaster risk management strategy, and have the potential to play an important role in disaster risk reduction" (p. 3). As such, it is imperative that households invest in protective measures prior to a natural disaster by participating in insurance programmes.²⁸

While natural disasters cause substantial economic damages and adversely impact the domestic economy, they are commonly described as a low-probability event.²⁹ Thus, many individuals often elect not to purchase insurance because the probability that a natural disaster occurs is significantly low.³⁰ In this context, residents neglect to account for the impending natural disaster losses, since they estimate that natural disasters are low-probability events.²⁴ As such, Kunreuther⁵ indicates that the general public may not invest in appropriate protective measures because they assume that the cost of the insurance exceeds the benefits of protective measures.

Also, Anderson³¹ suggests that households decide not to insure against natural disasters, since these negative shocks are "confined to relatively concentrated areas" (p. 579). According to Schwarze and Wagner³⁰ the "systematic underestimation and high discounting of the full extent of the risk of rare disasters by those people likely to be affected" explains the considerably low demand for natural disaster insurance (p. 3).³² As a result, Kunreuther²⁹ explains that only a small number of residents willingly implement "cost-effective loss-reduction measures" before a natural disaster (p. 912).³³ It is also possible that the accessibility to international and domestic assistance may contribute to the lack of demand for insurance across countries.

Besides, the literature provides ample evidence that the convenience of foreign and local aid clarifies the disinclination of the general population to invest in effective protective policy measures against natural disasters.³⁴ In this context, Coate³⁵ argues

³⁰ Schwarze and Wagner (2007).

- ³² Kunreuther (1996) also suggests that "underestimation of probability" and "high discount rates" describe the motives residents may not invest in protective measures prior to a natural disaster.
- ³³ In addition, Kunreuther (1984, 1996, 2008) provides a great discussion on the reasons why individuals underinsure from natural disaster losses.

³⁴ See, for example, Coate (1995); Kunreuther (1996); Schwarze and Wagner (2007).

³⁵ Coate (1995).

²⁴ Kunreuther (1984).

²⁵ Athavale and Avila (2011).

²⁶ Zeckhauser (1995).

²⁷ Arnold (2008).

²⁸ Kriesel and Landry (2004).

²⁹ Kunreuther (2008).

³¹ Anderson (1974).

that this "charitable assistance" causes significant "inequities and inefficiencies" in the domestic economy (p. 47).³⁶ Also, Raschky *et al.*³⁷ argue that the institutional structure of government assistance programmes considerably impacts insurance demand. Furthermore, Kunreuther⁵ and Schwarze and Wagner³⁰ note that many households presume and anticipate assistance following a natural disaster and, therefore, decide not to purchase insurance.

However, it is important to note that many households are generally more likely to purchase natural disaster insurance following an occurrence of a natural disaster as compared with before this negative shock.³⁸ This is because the incidence of the natural disaster becomes "more salient in people's minds due to the availability bias and/or there is more concern by individuals about the event and a desire to invest in protection"³⁹(p. 94). Moreover, Gennaioli and Shleifer⁴⁰ explain that there is preferred recollection of information, since the likelihood that a natural disaster occurs is low—"representativeness heuristics" (p. 1430). Nevertheless, this negative shock develops into an account of an uncertain event as soon as it takes place, which, in turn, causes many individuals to purchase natural disaster insurance.⁴⁰

Moreover, Kunreuther⁴¹ discusses four important "cost bearing" methods to secure protection from natural disaster losses: (1) "total federal responsibility", (2) "self insurance by the homeowner", (3) "required insurance protection", and (4) "land-use restrictions and building codes" (p. 287). Nevertheless, Kunreuther⁴¹ suggests that an adequate protective measure entails a complete natural disaster insurance protection complemented with land-use and building codes regulations in order to mitigate economic damages caused by natural disasters. According to Gerber,⁴² insufficient and ineffective protective measures prior to a natural disaster may exacerbate the detrimental consequences of natural disasters.

Determinants of insurance market development

The literature has documented that national income is a critically important determinant of insurance consumption in a country.⁴³ More specifically, higher income is associated with insurance market development, as, for example, argued by

³⁶ Furthermore, Coate (1995) explains that the unwillingness of the general public to invest in protective measures (i.e. purchase natural disaster insurance) from natural disasters is considerably associated with the conventional charity of the population concerning those individuals that are greatly affected by natural disasters in the United States.

³⁷ Raschky et al. (2013).

³⁸ Cutler and Zeckhauser (2004); Kunreuther and Pauly (2005).

³⁹ Kunreuther and Pauly (2005).

⁴⁰ Gennaioli and Shleifer (2010).

⁴¹ Kunreuther (1974).

⁴² Gerber (2007).

 ⁴³ Hammond *et al.* (1967); Beenstock *et al.* (1986); Truett and Truett (1990); Browne and Kim (1993);
 Outreville (1996); Enz (2000); Browne *et al.* (2000); Ward and Zurbruegg (2002); Beck and Webb (2003);
 Esho *et al.* (2004); Hussels *et al.* (2005); Hwang and Greenford (2005); Li *et al.* (2007); Feyen *et al.* (2011).

Browne *et al.*⁴⁴ This is the case because greater income enables households to purchases insurance to acquire financial protection.⁴⁵ Furthermore, Li *et al.*⁴⁶ suggest that a "large income results in a greater loss of expected utility for the dependents in the event of the income earner's death" and thus increases life insurance consumption in an economy (p. 640).

Next, several studies have emphasised the significance of inflation rates as an imperative economic factor in insurance market determination.⁴⁷ In particular, a rising inflation rate is anticipated to reduce the demand for insurance products. Outreville⁴⁸ therefore indicates that insurance products may not effectively provide for the welfare of the general population in high inflation-rate economies. Hussels *et al.*⁷ explain that higher inflation rates reduce the total value of all forthcoming repayments from the insurance industry. Hence, higher inflation rates decrease the benefits of insurance products and, therefore, inhibit the purchase of insurance policies in a country.^{49,50}

It is also imperative to account for the real interest rates in an economy. However, the literature has not established the relationship between real interest rates and insurance market development.⁵¹ Beck and Webb⁵² argue that higher real interest rates are associated with greater insurance consumption. This is the case as rising real interest rates contribute to greater investment returns for the insurance companies, which, in turn, may supply higher profitability to their customers.⁵² Li *et al.*⁴⁶ also explain that higher real interest rates may reduce the price of insurance policies, and, thus, increase insurance consumption. However, rising real interest rates may also induce prospective purchasers of insurance products to decrease "their number of purchases" due to expectations of greater investment returns.^{46,53}

Furthermore, the literature has emphasised the critical impact of government provisions, i.e. government spending on social welfare, on insurance consumption.⁵⁴ It is anticipated that households normally decrease their investment in protective measures (i.e. purchase life insurance) given that the government is allocating more resources towards social welfare programmes.⁵⁵ Nevertheless, the relationship between government expenditures on social welfare and insurance market development is

⁴⁴ Browne *et al.* (2000).

⁴⁵ Feyen *et al.* (2011).

⁴⁶ Li et al. (2007).

⁴⁷ Browne and Kim (1993); Outreville (1996); Browne *et al.* (2000); Ward and Zurbruegg (2002); Beck and Webb (2003); Esho *et al.* (2004); Hussels *et al.* (2005); Li *et al.* (2007); Feyen *et al.* (2011).

⁴⁸ Outreville (1996).

⁴⁹ Ward and Zurbruegg (2002).

⁵⁰ Ward and Zurbruegg (2002) also note that rising inflation rates are considerably linked with macroeconomic volatility, which, in turn, devalues the benefits of financial resources, that is, insurance products.

⁵¹ Outreville (1996); Beck and Webb (2003); Li et al. (2007); Feyen et al. (2011).

⁵² Beck and Webb (2003).

⁵³ Feyen *et al.* (2011) explain that the relationship between real interest rates and insurance consumption is often not straightforward since the supply and demand for insurance policies are extremely intricate.

⁵⁴ Browne and Kim (1993); Outreville (1996); Ward and Zurbruegg (2002); Beck and Webb (2003); Zietz (2003); Hussels *et al.* (2005); Hwang and Greenford (2005); Li *et al.* (2007); Feyen *et al.* (2011).

⁵⁵ Ward and Zurbruegg (2002); Hussels et al. (2005).

unclear.⁵⁶ For example, Browne and Kim⁵⁷ provide evidence that government spending on social welfare is significantly associated with higher demand for life insurance.⁵⁸

Moreover, it is significant to control for the dependency ratio in the analysis of insurance consumption.⁵⁹ More specifically, the primary goal of acquiring life insurance is to secure financial protection for dependents in the event of an untimely death of the primary wage earner as first documented by Hammond *et al.*^{60,61} However, Beck and Webb⁵² argue that a rise in the dependency ratio suggests that a sizeable proportion of the general public are extremely youthful to invest in savings for retirement, which, in turn, leads to a decrease in demand for savings products, that is, life insurance policies.

In addition, it is important to account for the political environment of a country in the analysis of insurance consumption.⁶² Ward and Zurbruegg⁴⁹ emphasise that the legal environment in the local economy is an important factor of the growth of life insurance premiums. Similarly, Esho *et al.*⁶³ explain the significance of the legal environment in explaining property-casualty insurance. This is the case because countries that experience a high quality of legal environment provide the general population with protection against the inappropriate activities of insurance corporations.⁴⁹ As such, we anticipate that countries with low levels of political risk experience greater insurance market development.

Finally, it is imperative to consider the interaction effects of natural disasters and political risk, as these two factors may possibly interact in influencing insurance market development across countries. Oh and Reuveny¹⁰ argue that natural disasters and political risk may possibly influence each other. It is possible that the occurrence of natural disasters leads to political unrest in a country. For example, Olson and Drury,⁶⁴ and Drury and Olson⁶⁵ find that natural disasters increase political instability in a society, while Bhavnani,⁶⁶ Brancati,⁶⁷ and Nel and Righarts⁶⁸ show that natural

⁵⁶ For a more comprehensive discussion on the relationship between governments' expenditures on social welfare and insurance consumption, see Browne and Kim (1993) and Zietz (2003).

⁵⁷ Browne and Kim (1993).

⁵⁸ Browne and Kim (1993) indicate that these government benefits denote "assets which individuals protect against premature loss" (p. 627).

⁵⁹ Hammond *et al.* (1967); Campbell (1980); Beenstock *et al.* (1986); Truett and Truett (1990); Browne and Kim (1993); Outreville (1996); Ward and Zurbruegg (2002); Beck and Webb (2003); Zietz (2003); Hussels *et al.* (2005); Hwang and Greenford (2005); Li *et al.* (2007); Feyen *et al.* (2011).

⁶⁰ Hammond *et al.* (1967).

⁶¹ Also, Campbell (1980) provides a detailed theoretical analysis on the demand for life insurance, particularly households' efficient response to the potential early death of the primary wage earner.

⁶² Browne *et al.* (2000); Ward and Zurbruegg (2002); Esho *et al.* (2004); Hussels *et al.* (2005); Feyen *et al.* (2011).

⁶³ Esho *et al.* (2004).

⁶⁴ Olson and Drury (1997).

⁶⁵ Drury and Olson (1998).

⁶⁶ Bhavnani (2006).

⁶⁷ Brancati (2007).

⁶⁸ Nel and Righarts (2008).

disasters intensify intrastate conflict in a country. Berrebi and Ostwald⁶⁹ also find that natural disasters increase terrorism occurrences. Moreover, Chang and Berdiev⁷⁰ find that natural disasters increase the likelihood that a government is replaced.

As such, political unrest heightens uncertainty about the political future of the government (Klomp and de Haan, 2009). It is therefore possible that the occurrences of natural disasters contribute to lower insurance consumption under the tenure of a government with high levels of political risk. This is because political instability and powerful conflicts contribute to "uncertainty about future property rights which deters productive activities and, in particular, investment decisions".⁷¹(p. 19) Also, the general population may be unable to rely on insurance companies to provide financial protection in the event that a natural disaster causes the untimely death of the primary wage earner or contributes to considerable economic costs in countries with higher levels of political risk. Feyen *et al.*⁴⁵ highlight the value of the legal environment in the local economy, as it expands the reliability and trustworthiness of insurance companies. Hence, individuals are less likely to invest in protective measures against natural disasters (i.e. purchase insurance policies) to attain financial protection in countries with higher levels of political risk.

It is thus possible that the incidences of natural disasters and death attributed to natural disasters impact insurance consumption differently as the political risk level of a country rises. In particular, a rise in political risk may contribute to unfavourable environment for insurance market development, especially following a natural disaster. In our view, this is the case for responsive and unresponsive governments.⁷² Even an extremely responsive government is unable to provide effective natural disaster relief management. This is because governments may react to the occurrence of a natural disaster by commanding central planning in the allocation of public resources. In this context, Sobel and Leeson⁷³ argue that "central planning cannot effectively coordinate decision making among numerous and dispersed individuals with different endowments, wants, and needs" (p. 529). In the United States, for example, Sobel and Leeson⁷⁴ detail the incapacity of the Federal Emergency Management Agency to provide effective natural disaster assistance following Hurricane Katrina in 2005. It is therefore perhaps not surprising that individuals anticipate international assistance following a natural disaster, especially in countries with higher levels of political risk.

Data

The primary goal of the present paper is to examine the relationship between natural disasters, political risk and insurance market development. The analysis is based upon

⁶⁹ Berrebi and Ostwald (2011).

⁷⁰ Chang and Berdiev (2013).

⁷¹ Bellettini (1998).

⁷² Besley and Burgess (2002) emphasise that "mass media and open political institutions" significantly influence government responsiveness (p. 1445).

⁷³ Sobel and Leeson (2007).

⁷⁴ Sobel and Leeson (2006).

data recorded annually over the period 1984–2009 in a panel of 39 countries. The specific sets of countries are Algeria, Australia, Austria, Belgium, Canada, Colombia, Denmark, Egypt, Finland, France, Greece, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Luxembourg, Malaysia, Mexico, Morocco, the Netherlands, New Zealand, Norway, the Philippines, Portugal, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, the United Kingdom, the United States of America and Venezuela. The data is obtained from several sources, namely the Emergency Events Database⁷⁵ of the Centre for Research on the Epidemiology of Disasters (CRED), the International Country Risk Guide,⁷⁶ Swiss Reinsurance Company⁷⁷ and the World Bank's World Development Indicators (2011).

The data on life insurance premiums, non-life insurance premiums and total insurance premiums comes from Swiss Reinsurance Company.⁷⁷ To effectively characterise insurance market development across countries, we use life insurance premiums, non-life insurance premiums and total insurance premiums as a percentage of GDP (insurance penetration) and (log) per capita, in constant US\$ (insurance density). More specifically, we calculate (1) (log) real life insurance premiums per capita (life insurance density), (2) (log) real non-life insurance premiums per capita (non-life insurance density), (3) (log) real total insurance premiums per capita (total insurance density), (4) life insurance premiums as a percentage of GDP (life insurance penetration), (5) non-life insurance premiums as a percentage of GDP (non-life insurance penetration), and (6) total insurance premiums as a percentage of GDP (total insurance penetration).⁷⁸

Next, the data on natural disasters is taken from the Emergency Events Database (EM-DAT, 2011) of the CRED. This database records information using an extensive range of nationwide sources that detail and give an account of natural disaster occurrence since 1900.^{79,80} As such, this database classifies a "disaster as a natural situation or event which overwhelms local capacity, necessitating a request for external assistance"²¹(p. 222). More specifically, the EM-DAT registers a natural disaster if the full the following conditions: (1) "ten or more people reported killed"; (2) "100 or more people reported affected"; (3) "declaration of a state of emergency"; or (4) "a call for international assistance". Ramcharan⁸¹ explains that

⁷⁵ Emergency Events Database (2011).

⁷⁶ International Country Risk Guide (2010).

⁷⁷ Swiss Reinsurance Company (2011).

⁷⁸ Since the data on the insurance premiums are reported in local currency units, Swiss Reinsurance Company uses the average period exchange rate to convert all time series into U.S. dollars. Next, we use the total population and U.S. consumer price index data from the World Bank's World Development Indicators (2011) to transform the data on insurance premiums into real per capita variables (insurance density). We also use the data on GDP that come from the World Bank's World Development Indicators (2011) to express the insurance premiums variables as a percentage of GDP (insurance penetration).

⁷⁹ Raddatz (2007); Noy (2009); Oh and Reuveny (2010).

⁸⁰ Noy (2009) explains that these sources consist of non-governmental institutions, United Nations organisations, research institutions, insurance corporations and the media.

⁸¹ Ramcharan (2007).

"these relatively low thresholds ensure that most disasters are recorded in the database" (p. 34). Furthermore, this database has been used extensively in recent studies on natural disasters.⁸²

To ensure the robustness of our results, we use five measures of natural disaster variables in the empirical analysis, namely, floods, earthquakes, windstorms, epidemics and climatological disasters. To measure the incidences of natural disasters, we employ the number of floods, earthquakes, windstorms, epidemics and climatological disasters that occurred in a particular year t and country i. To effectively quantify natural disaster deaths, we utilise the total number of "persons confirmed as dead and persons missing and presumed dead" caused by floods, earthquakes, windstorms, epidemics and climatological disasters in a particular year t and country i. As such, we use five natural disaster variables to evaluate the occurrences (number) of natural disasters across countries. In addition, we employ five natural disaster variables to assess natural disaster deaths across countries.

The discussion in the previous section on the determinants of insurance market development suggests incorporating additional explanatory variables to obtain efficient estimation results. As such, we follow previous literature and employ real GDP per capita (constant 2000 US\$ and transformed into natural logarithms), annual percentage change in consumer price index to denote the inflation rate, lending interest rates (adjusted for inflation by the GDP deflator) to represent the real interest rates, government health expenditure as a percentage of GDP to measure government provision on social welfare,⁸³ and the ratio of the population under the age of 15 to the population aged 15–65 to capture the dependency ratio. All these variables are extracted from the World Bank's World Development Indicators (2011).

The data on political risk comes from the International Country Risk Guide,⁷⁶ which constructs an index of political risk covering 12 main dimensions: government stability (0-12), socioeconomic conditions (0-12), investment profile (0-12), internal conflict (0-12), external conflict (0-12), corruption (0-6), military in politics (0-6), religious tensions (0-6), law and order (0-6), ethnic tensions (0-6), democratic accountability (0-6), and bureaucracy quality (0-4).⁸⁴ These sub-indexes are, in turn, aggregated into one single index of political risk. The political risk index ranges between 0 and 100, where lower values represent greater political risk.⁸⁵ The definitions, data sources, predicted signs and summary statistics for all the variables are displayed in Table A1 (in Appendix).

⁸² See, for example, Kahn (2005); Bhavnani (2006); Raddatz (2007); Ramcharan (2007); Nel and Righarts (2008); Noy (2009); Oh and Reuveny (2010); Strobl (2012); Chang and Berdiev (2013).

⁸³ Previous literature has also employed social security expenditures to capture government provision on social welfare (see, for example, Li *et al.*, 2007). However, using social security expenditures would have reduced the number of observations in our empirical analysis.

⁸⁴ The weights for each sub-index that is used to construct the political risk index are in parenthesis.

⁸⁵ For a detailed analysis on the political risk index, including construction and methodology, see International Country Risk Guide (2010).

Model

Consider the following dynamic panel data model, which improves and corrects many of the shortcomings resulting from the cross-sectional and static panel data methodology:

$$y_{it} = \alpha y_{i,t-1} + \beta \operatorname{disaster}_{it} + \delta' x_{it} + \mu_i + \eta_t + \varepsilon_{it} \ i = 1, \dots, N \quad t = 1, \dots, T,$$
(1)

where y_{it} is the dependent variable that represents insurance density (life insurance density, non-life insurance density and total insurance density) and insurance penetration (life insurance penetration, non-life insurance penetration and total insurance penetration). The explanatory variable, *disaster*, corresponds to the five measures of natural disasters, specifically (the number of and deaths caused by) floods, earthquakes, windstorms, epidemics and climatological disasters. X denotes a set of independent variables, which includes real GDP, the inflation rate, the real interest rate, health expenditure and the dependency ratio; μ_i are the unobserved country-specific effects, η_t are the time-specific effects, ε_{it} is the disturbance term, and *i* and *t* represent the country and time period, respectively.

However, the lagged dependent variable is correlated with the error term when the ordinary least square model is employed in the estimation. We therefore use a dynamic panel GMM model developed by Arellano and Bond,¹³ Arellano and Bover,¹⁴ and Blundell and Bond,¹⁵ who proposed a methodology to generate consistent and efficient estimators in dynamic panel data models. More specifically, we first-difference Eq. (1) to eliminate the country-specific effects, and, thus, generate the first-difference GMM¹³ model as follows:

$$\Delta y_{it} = \alpha \Delta y_{i,t-1} + \beta \Delta disaster_{it} + \delta' \Delta x_{it} + (\eta_t - \eta_{t-1}) + \Delta \varepsilon_{it}, \tag{2}$$

where Δ denotes first-difference. The limitation of the first-difference GMM estimator is that it eliminates "the pure cross-country dimension of the data" and reduces "the signal-to-noise ratio, thereby exacerbating measurement error biases".¹⁷(p. 278) Arellano and Bover,¹⁴ and Blundell and Bond¹⁵ thus propose the system GMM estimator that stacks the level and difference equations, and uses the lagged levels of the series (y_{it},x_{it}) as instruments for first-differenced variables ($\Delta y_{i,t-1},\Delta x_{it}$), and lagged first-differenced of the series (y_{it-1},x_{it-1}) as instruments for the level variables.⁸⁶

As such, we generate the dynamic two-step system GMM estimators, where "the error terms are assumed to be both independent and homoskedastic, across countries and over time" in the first step and, subsequently, "the residuals obtained in the first step are used to construct a consistent estimate of the variance-covariance matrix,

⁸⁶ We employ the second lag of the variable inflation rate as an instrument. Also, we utilise year fixed effects as standard instruments in our model. In the earlier draft of this paper, we also employed all available lagged values of independent variables as instruments (as in Beck *et al.*, 2000). As a way to minimise the number of instruments in the regressions, we collapse the matrix of instruments as suggested in Roodman (2009). Overall, the results continue to support our findings. All these results are available upon request.

thus relaxing the assumptions of independence and homoskedasticity" in the second step.¹⁷ (p. 278)

Furthermore, we extend Eq. (2) and examine the impact of political risk and the interaction effects of natural disasters and political risk on insurance market development. Hence, we investigate the following model:

$$\Delta y_{it} = \alpha \Delta y_{i,t-1} + \beta \Delta disaster_{it} + \lambda \Delta [disaster_{it} \times risk_{it}] + \rho \Delta risk_{it} + \delta' \Delta x_{it} + (\eta_t - \eta_{t-1}) + \Delta \varepsilon_{it}, \qquad (3)$$

where the explanatory variable, *risk*, represents the political risk of a country and $[disaster_{it} \times risk_{it}]$ captures the interaction effects of natural disasters and political risk. To ensure that our specified econometric model produces consistent, efficient and robust estimates, we conduct a number of specification tests: the Hansen and Arellano–Bond tests. The Hansen test of over-identification restrictions tests the validity of the instruments, whereas the Arellano–Bond tests of first-order and second-order autocorrelation tests that the estimated residuals do not produce first-order and second-order serial correlation, respectively. In what follows, we provide the dynamic panel two-step system GMM regression estimates for Eqs (2) and (3) and discuss these empirical results.

Empirical results

Baseline specification

The GMM regression estimates for the dependent variables' total insurance density (columns 1–5), life insurance density (columns 6–10) and non-life insurance density (columns 11–15) are presented in Table 1. In Table 2, we provide the GMM regression estimates for the dependent variables' total insurance penetration (columns 1–5), life insurance penetration (columns 6–10) and non-life insurance penetration (columns 11–15). In Tables 1 and 2, the natural disaster variables are the number of natural disasters, namely epidemic, flood, climatological disasters, earthquake and windstorm that occurred. As can be seen, each natural disaster variable is entered one at a time for each dependent variable in the empirical model. To start, the lagged dependent variable is positive and statistically significant at the 5 per cent level in all equations. These findings indicate that countries that experienced high levels of insurance consumption in the past will continue to experience high insurance consumption in the future.

Consider next the effect of the natural disaster variables on total insurance density (columns 1-5) in Table 1. We find that the natural disaster variables epidemic, flood and windstorm are positive and statistically significant at the 5 per cent level, suggesting that an increase in these natural disaster variables is associated with higher total insurance density. Next, we estimate the GMM model distinguishing between life insurance density and non-life insurance density in our empirical analysis. More specifically, we examine the impact of the natural disaster variables on life insurance density (columns 6-10) and non-life insurance density (columns 11-15) in Table 1. Our results provide evidence that all five natural disaster variables are positive and

		To	tal insurance de	nsity			
	(1)	(2)	(3)	(4)	(5)		
Lagged dependent variables	0.559**	0.577**	0.543**	0.503**	0.521**		
Epidemic (number)	(20.437) 0.020** (2.812)	(13.286)	(12.718)	(16.602)	(16.910)		
Flood (number)	(2.012)	0.015** (3.621)					
Climatological (number)		(5.021)	0.031 (0.348)				
Earthquake (number)			(0.340)	0.013 (1.184)			
Windstorm (number)				(1.104)	0.012**		
Real GDP	0.145 (1.203)	0.226 (1.488)	0.245* (1.778)	0.141 (1.150)	(4.152) 0.128 (1.043)		
Inflation rate	-0.021 (-1.315)	-0.043^{**} (-3.233)	-0.025^{*} (-1.674)	-0.034^{**} (-2.374)	-0.019 (-1.109)		
Interest rate	-0.016 (-1.116)	0.006 (0.288)	0.013 (0.657)	-0.002 (-0.146)	-0.006 (-0.359)		
Health expenditure	0.053 (0.639)	-0.012 (-0.075)	-0.100 (-0.946)	-0.019 (-0.173)	-0.047 (-0.427)		
Dependency ratio	-0.381 (-1.624)	0.095 (0.152)	-0.694^{**} (-2.348)	-0.456 (-1.645)	-0.336 (-1.346)		
Arellano–Bond test (1) Arellano–Bond test (2) Hansen test	0.032 0.221 0.115	0.002 0.223 0.110	0.001 0.378 0.110	0.002 0.100 0.111	0.021 0.145 0.114		
	Life insurance density						
	(6)	(7)	(8)	(9)	(10)		
Lagged dependent variables	0.589**	0.590**	0.591**	0.597**	0.592**		
Epidemic (number)	(2.468) 5.913**	(2.871)	(1.116)	(1.381)	(6.845)		
Flood (number)	(10.329)	10.577** (24.632)					
Climatological (number)		(21.052)	26.789** (18.567)				
Earthquake (number)			()	3.511** (9.657)			
Windstorm (number)					10.473** (20.129)		
Real GDP	4.630** (4.602)	2.289** (22.386)	2.242** (8.893)	5.744** (6.309)	6.498** (3.700)		
Inflation rate	-8.871^{**} (-8.208)	(-9.876^{**}) (-7.618)	(-1.556^{**}) (-5.972)	-4.568^{**} (-9.056)	-3.783^{**} (-5.055)		
Interest rate	(-8.208) -34.429^{**} (-58.809)	(-74.649)	(-3.972) -46.717** (-87.943)	(-9.030) -46.754** (-96.108)	(-3.033) -49.808** (-44.959)		

 Table 1
 GMM regression estimates: Insurance density

Table 1 (continued)

-		Lij	fe insurance den.	sity	
	(6)	(7)	(8)	(9)	(10)
Health expenditure	-1.854**	-2.802**	-2.750**	-1.452**	-0.721
	(-4.041)	(-2.520)	(-6.253)	(-3.548)	(-1.487)
Dependency ratio	-1.321**	-3.948**	-1.670**	-2.478**	-1.963 **
	(-5.149)	(-3.747)	(-6.527)	(-2.565)	(-2.783)
Arellano-Bond test (1)	0.002	0.003	0.000	0.012	0.002
Arellano–Bond test (2)	0.366	0.339	0.377	0.390	0.323
Hansen test	0.182	0.293	0.163	0.187	0.190
		Non-	-life insurance de	ensity	
	(11)	(12)	(13)	(14)	(15)
Lagged dependent variables	0.520**	0.515**	0.525**	0.521**	0.524**
	(5.871)	(5.926)	(5.325)	(5.394)	(5.563)
Epidemic (number)	5.595**		× /	× /	
	(30.352)				
Flood (number)	()	5.188**			
		(14.296)			
Climatological (number)			3.434**		
			(15.090)		
Earthquake (number)			(2.654**	
				(4.018)	
Windstorm (number)				(1.272**
					(3.188)
Real GDP	6.768**	7.881**	13.153**	13.087**	12.059**
	(2.814)	(2.633)	(5.576)	(3.586)	(5.391)
Inflation rate	-6.332**	-4.727**	-5.474**	-5.872**	-5.808**
	(-22.297)	(-12.263)	(-17.599)	(-23.934)	(-23.179)
Interest rate	-17.998**	-22.295**	-17.369**	-17.987**	-18.162**
	(-33.539)	(-32.104)	(-25.466)	(-38.744)	(-37.953)
Health expenditure	2.347**	7.827**	2.113**	2.149**	1.612**
fitearai enpenditare	(6.442)	(7.577)	(4.238)	(8.153)	(6.893)
Dependency ratio	-6.896**	-9.544**	-8.275**	-3.155	-6.357**
	(-6.864)	(-4.040)	(-5.604)	(-1.272)	(-3.316)
Arellano-Bond test (1)	0.001	0.001	0.001	0.000	0.002
Arellano–Bond test (2)	0.178	0.133	0.192	0.123	0.145
Hansen test	0.129	0.113	0.112	0.125	0.126
	0.127	0.115	0.110	0.151	0.120

Notes: The natural disaster variables correspond to the incidences (number) of natural disasters that occurred. The regressions include a constant term. The *t*-values are in parentheses. ****** and ***** indicate the statistical significance at the 5 per cent and 10 per cent levels, respectively.

statistically significant at the 5 per cent level in the life insurance and non-life insurance density specifications, indicating that an increase in any of these natural disaster variables contributes to greater life insurance and non-life insurance density.

Furthermore, we analyse the impact of these natural disaster variables on total insurance penetration (columns 1-5) in Table 2. The results suggest that the natural

		Tot	al insurance pen	etration	
	(1)	(2)	(3)	(4)	(5)
Lagged dependent variable	s 0.595**	0.526**	0.560**	0.541**	0.539**
Epidemic (number)	(16.995) 0.001** (2.146)	(24.223)	(28.241)	(18.750)	(48.095)
Flood (number)	(2.146)	0.14×10^{-3}	*		
		(3.755)	4		
Climatological (number)			0.23×10^{-4} * (2.044)	*	
Earthquake (number)			(2.044)	0.157×10^{-1} (0.519)	-4
Windstorm (number)				(0.515)	0.33×10^{-3} ** (2.910)
Real GDP	0.002	0.001	-0.001	0.002	0.002**
	(0.593)	(0.472)	(-0.384)	(0.919)	(2.926)
Inflation rate	0.53×10^{-1}	$^{-4}$ -0.235×10^{-4}	$-0.49 \times 10^{-4*}$	* -0.45 × 10 ⁻³	
initiation face	(-0.211)	(-0.079)	(-2.216)	(-1.884)	(-3.083)
Interest rate	0.53×10^{-10}		0.455×10^{-4}		
Interest fate	(-0.283)	(0.089)	(1.265)	(0.487)	(1.154)
Health expenditure		· /		· /	
Health expenditure	0.006*	0.001	0.001	0.002	0.002
D 1	(1.936)	(0.230)	(0.251)	(0.536)	(1.406)
Dependency ratio	-0.005	-0.014*	-0.004	-0.003	-0.010
	(-1.208)	(-1.686)	(-0.752)	(-0.569)	(-1.515)
Arellano–Bond test (1)	0.003	0.000	0.001	0.001	0.001
Arellano–Bond test (2)	0.355	0.332	0.323	0.348	0.322
Hansen test	0.464	0.381	0.507	0.420	0.320
		Lif	e insurance pene	tration	
	(6)	(7)	(8)	(9)	(10)
Lagged dependent variables	s 0.561**	0.595**	0.591**	0.501**	0.505**
	(68.919)	(99.915)	(70.239)	(81.361)	(23.142)
Epidemic (number)	0.46×10^{-1} (2.308)	3**			× ,
Flood (number)	· · /	$0.10 imes 10^{-4}$	**		
		(3.107)			
Climatological (number)			0.18×10^{-3}	**	
Earthquake (number)			(2.410)	0.11×10^{-2}	3**
Lartiquake (number)				(4.914)	
Windstorm (number)					0.38×10^{-3} *
Real GDP	-0.001	0.002**	0.002**	0.0028*	(1.716) 0.001*
Real ODI	(-0.761)	(3.546)	(3.394)	(4.137)	(1.732)
Inflation rate		$^{-4}$ -0.43×10^{-3}		(4.137) -0.37×10^{-2}	
				(-2.952)	(1.283)
Interest rate	0.268 × 10	(-3.858) $-3 -0.04 \times 10^{-3}$	** -0.42×10^{-3}	** -0.26×10^{-3}	$^{3**} -0.93 \times 10^{-4}$
	(0.567)	(-2.603)	(-3.803)	(2.753)	(-0.383)
	· /	× /	. ,	× /	· · · ·

Table 2 GMM regression estimates: Insurance penetration

Table 2 (continued)

		L	ife insurance per	netration	
	(6)	(7)	(8)	(9)	(10)
Health expenditure	0.004	0.002**	0.003**	0.003*	0.003**
	(1.386)	(2.146)	(3.280)	(1.879)	(3.115)
Dependency ratio	-0.008	-0.004 **	-0.003*	-0.006^{**}	-0.002
	(-1.620)	(-2.731)	(-1.769)	(-2.144)	(-0.756)
Arellano-Bond test (1)	0.000	0.000	0.001	0.002	0.000
Arellano–Bond test (2)	0.384	0.311	0.330	0.376	0.337
Hansen test	0.213	0.217	0.359	0.408	0.241
		Non	-life insurance p	enetration	
	(11)	(12)	(13)	(14)	(15)
Lagged dependent variabl	es 0.583**	0.571**	0.581**	0.564**	0.589**
	(93.620)		(55.188)	(56.288)	(64.013)
Epidemic (number)	0.98×10^{-4}	4**	. ,	· · · ·	· /
1 ()	(1.974)				
Flood (number)		0.638×10^{-1}	-3*		
		(1.933)			
Climatological (number)			0.21×10^{-1}	4**	
e ()			(2.183)		
Earthquake (number)				0.12×10^{-3}	3**
• • • •				(4.899)	
Windstorm (number)				· · · ·	0.14×10^{-4} **
× ,					(4.258)
Real GDP	0.001**	0.002**	0.001*	0.001**	0.001**
	(2.101)				
Inflation rate	-0.746×10^{-10}	$^{-4}$ -1.74×10^{-3}	$^{3^{**}}$ -0.127 × 10	$^{-3}$ -0.114×10^{-3}	$\begin{array}{c} (2.188) \\ -3 & -0.21 \times 10^{-3^{**}} \end{array}$
	(-0.625)	(-2.158)		(-0.899)	(-2.844)
Interest rate	0.194×10^{-1}	$^{-3}$ 0.194 \times 10 ⁻	$^{-3}*$ 0.703 × 10	$^{-4}$ -0.468×10^{-1}	
	(1.033)	(1.782)	(0.821)	(-0.020)	(1.954)
Health expenditure	0.001**	0.002**	0.001**	0.001**	0.001**
T	(2.980)	(2.568)	(2.553)	(2.852)	(3.243)
Dependency ratio	-0.004**	-0.006**	-0.004**	-0.005**	-0.004**
1 ··· · J ··· ·	(-2.418)	(-2.235)	(-2.364)	(-2.445)	(-2.599)
Arellano–Bond test (1)	0.002	0.001	0.000	0.021	0.000
Arellano–Bond test (2)	0.222	0.123	0.233	0.212	0.245
Hansen test		0.176	0.115	0.150	
Hansen test	0.115	0.176	0.115	0.150	0.120

Notes: The natural disaster variables correspond to the incidences (number) of natural disasters that occurred. The regressions include a constant term. The *t*-values are in parentheses. ****** and ***** indicate the statistical significance at the 5 per cent and 10 per cent levels, respectively.

disaster variables epidemic, flood, climatological and windstorm are positive and statistically significant at conventional levels, indicating that an increase in these natural disaster variables leads to higher total insurance penetration. However, it seems that the natural disaster variable earthquake has a limited impact on total insurance penetration, which is evident from the statistically insignificant coefficient (column 4) in Table 2. As before, we re-estimate the GMM model, differentiating between life insurance penetration and non-life insurance penetration. We find that a rise in these five natural disaster variables significantly increases life insurance and non-life insurance penetration. Overall, our findings clearly support the notion that the incidence of natural disasters contributes to higher insurance consumption as documented by Kunreuther.⁵

Next, we investigate whether deaths caused by these five natural disaster variables play a role in insurance market development. The GMM regression estimates for the dependent variables total insurance density (columns 1–5), life insurance density (columns 6–10) and non-life insurance density (columns 11–15) are presented in Table 3, whereas the GMM regression estimates for the dependent variables total insurance penetration (columns 1–5), life insurance penetration (columns 1–5), life insurance penetration (columns 1–5), are displayed in Table 4. We find that deaths attributable to epidemic, flood and climatological disasters are associated with higher total insurance density, at least at the 10 per cent level of statistical significance. Moreover, we provide evidence that deaths caused by epidemic, flood, earthquake and climatological disasters significantly contribute to greater life insurance and non-life insurance density.

As before, we examine whether deaths attributable to these five natural disaster variables impact total insurance penetration (columns 1–5) in Table 4. We discover that deaths caused by all five natural disaster variables significantly lead to higher total insurance penetration. These effects are also similar in the non-life insurance penetration model. However, our findings indicate that deaths caused by only epidemic and climatological disasters are associated with higher life insurance penetration. Since natural disasters cause considerable human losses, our results are perhaps surprising, particularly for the life insurance penetration model. This is because life insurance may provide financial protection for the family in the event that a natural disaster causes the untimely death of the primary wage earner. Overall, we provide evidence that deaths attributable to most natural disasters contribute to higher insurance consumption.

We now turn to investigate the impact of the control variables on insurance consumption. The variable real GDP is positive and statistically significant at conventional levels in most equations in Tables 1–4, indicating that higher national per capita income is associated with insurance market development, including life insurance and non-life insurance. These findings are in line with those of Hammond *et al.*,⁶⁰ Beenstock *et al.*,⁸⁷ Truett and Truett,⁸⁸ Browne and Kim,⁵⁷ Outreville,⁴⁸ Enz,⁸⁹ Ward and Zurbruegg,⁴⁹ Beck and Webb,⁵² Hwang and Greenford,⁹⁰ Li *et al.*,⁴⁶ and Feyen *et al.*,⁴⁵ who find that an increase in national income leads to greater life insurance consumption. Also, these results are consistent with those of Beenstock *et al.*,⁹¹ Enz⁸⁹, Browne *et al.*,⁴⁴ Esho *et al.*,⁶³ and Feyen *et al.*,⁴⁵

⁸⁷ Beenstock *et al.* (1986).

⁸⁸ Truett and Truett (1990).

⁸⁹ Enz (2000).

⁹⁰ Hwang and Greenford (2005).

⁹¹ Beenstock *et al.* (1988).

	Total insurance density				
	(1)	(2)	(3)	(4)	(5)
Lagged dependent variables	s 0.654**	0.664**	0.667**	0.665**	0.666**
Epidemic (death)	(8.959) 0.779×10^{-1} (1.755)	(4.794) 4*	(4.445)	(7.365)	(5.773)
Flood (death)	(1.755)	0.473×10^{-5} (4.078)	ō**		
Climatological (death)		()	0.143×10^{-4}	4**	
Earthquake (death)			(2.453)	0.229×10	-6
Windstorm (death)				(0.824)	-0.296×10^{-5} (0.377)
Real GDP	0.082	0.023	0.038	0.010	0.032
Inflation rate	(1.013) -0.036**	(0.409) -0.036**	(0.657) -0.037**	(0.186) -0.039**	(0.497) -0.039**
Interest rate	(-3.344) -0.037** (-2.885)	(-2.584) -0.038** (-3.233)	(-3.116) -0.036** (-3.251)	(-2.989) -0.040^{**} (-3.131)	(-3.591) -0.040** (-3.274)
Health expenditure	(-0.013) (-0.187)	0.077 (0.844)	0.029 (0.489)	0.098 (1.099)	0.055 (0.978)
Dependency ratio	-0.112 (-0.695)	-0.059 (-0.398)	-0.148 (-0.883)	-0.045 (-0.315)	-0.090 (-0.681)
Arellano–Bond test (1)	0.000	0.001	0.000	0.001	0.000
Arellano–Bond test (2) Hansen test	0.116 0.223	0.211 0.214	0.223 0.329	0.135 0.323	0.222 0.310
			Life insurance a	lensity	
	(6)	(7)	(8)	(9)	(10)
Lagged dependent variabl	es 0.694	** 0.654**	* 0.695**	0.655**	0.695**
Epidemic (death)	(6.587 0.062	**	(7.807)	(8.482)	(6.492)
Flood (death)	(6.685) 0.003** (19.851)	*		
Climatological (death)		()	0.010** (16.553)		
Earthquake (death)				0.035** (5.885)	
Windstorm (death)					0.346×10^{-3} (0.141)
Real GDP	6.399			9.046**	6.422**
Inflation rate	(14.063 -4.337	** -11.377*		(16.107) -10.128** (27.100)	(11.863) -2.489** (-2.527)
Interest rate	(-12.149 -46.120 (-15.965))	** -44.520*	$\begin{array}{c} (-13.842) \\ * & -44.098^{**} \\ (-44.098) \end{array}$	(-27.109) -46.820 (-1.080)	(-3.527) -4.756 (-1.070)

Table 3 GMM regression estimates: Insurance density

		Life insurance density						
	(6)	(7)	(8)	(9)	(10)			
Health expenditure	26.437**	89.644**	27.484**	45.773**	25.396**			
	(8.062)	(8.390)	(6.153)	(24.735)	(3.733)			
Dependency ratio	-1.758**	-8.482^{**}	-1.714**	-0.874 **	-1.872**			
	(-8.613)	(-9.854)	(-2.078)	(-5.234)	(-3.054)			
Arellano-Bond test (1)	0.001	0.001	0.001	0.001	0.001			
Arellano-Bond test (2)	0.323	0.323	0.333	0.323	0.332			
Hansen test	0.165	0.284	0.245	0.224	0.162			
		Non	n-life insurance d	lensity				
	(11)	(12)	(13)	(14)	(15)			
Lagged dependent variables	0.618**	0.618**	0.619**	0.619**	0.617**			
	(9.843)	(9.162)	(7.649)	(3.346)	(5.637)			
Epidemic (death)	0.013*							
	(1.870)							
Flood (death)		0.001**						
		(10.935)						
Climatological (death)			0.007**					
			(46.958)					
Earthquake (death)				0.001**				
				(3.240)				
Windstorm (death)					0.002			
					(0.522)			
Real GDP	4.716**	3.027**	5.014**	5.660**	-1.861			
	(4.482)	(2.187)	(2.180)	(3.011)	(-0.832)			
Inflation rate	-8.422 **	-8.115 **	-8.427 **	-8.488**	-8.502**			
	(-42.908)	(-32.313)	(-28.953)	(-63.990)	(-26.200)			
Interest rate	-21.229**	-21.359**	-20.450 **	-20.757**	-21.430**			
	(-56.320)	(-11.049)	(-42.569)	(-49.431)	(-33.608)			
Health expenditure	4.263	10.793*	8.546**	9.468**	8.534**			
	(1.015)	(1.806)	(6.178)	(9.610)	(8.239)			
Dependency ratio	-2.977	-4.067	-1.667	-3.693	-2.414			
	(-0.570)	(-1.486)	(-0.303)	(-1.636)	(-0.679)			
Arellano-Bond test (1)	0.002	0.002	0.003	0.000	0.001			
Arellano-Bond test (2)	0.211	0.199	0.189	0.119	0.199			
Hansen test	0.257	0.238	0.263	0.217	0.221			

Table 3 (continued)

Notes: The natural disaster variables correspond to deaths caused by natural disasters. The regressions include a constant term. The *t*-values are in parentheses. ****** and ***** indicate the statistical significance at the 5 per cent and 10 per cent levels, respectively.

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		Tota	l insurance pene	tration	
	(1)	(2)	(3)	(4)	(5)
Lagged dependent variables	0.586**	0.563**	0.581**	0.544**	0.565**
Epidemic (death)	$(4.632) \\ 0.33 \times 10^{-5} * \\ (2.185)$	(4.412)	(9.003)	(3.120)	(3.945)
Flood (death)	(2.103)	0.12×10^{-6} ** (5.314)	*		
Climatological (death)		(0.01.)	0.17×10^{-6} * (1.707)		
Earthquake (death)			()	0.312×10^{-9} * (4.008)	*
Windstorm (death)				()	$0.11 \times 10^{-5^{**}}$ (2.204)
Real GDP	0.002 (1.247)	0.003* (1.923)	0.003 (1.551)	0.004* (1.865)	0.003 (1.430)
Inflation rate	-0.001^{**} (-4.806)	$(-0.48 \times 10^{-3})^{-3}$		$(1.005)^{\circ}$ 0.382×10^{-3} $(1.134)^{\circ}$	
Interest rate	(-0.210×10^{-4}) (-0.103)		0.211×10^{-3}	(-0.15×10^{-3}) (-0.568)	(-0.14×10^{-4}) (-0.081)
Health expenditure	-0.003^{*} (-1.739)	(-0.003*) (-1.794)	-0.005**	-0.003 (-1.478)	-0.003 (-1.628)
Dependency ratio	0.003 (0.659)	-0.003 (-0.565)	(2.200) 0.131×10^{-4} (0.002)		(-0.001) (-0.125)
Arellano–Bond test (1) Arellano–Bond test (2) Hansen test	0.000 0.209 0.375	0.001 0.503 0.531	0.001 0.543 0.377	0.000 0.458 0.503	0.002 0.432 0.583
		Life	e insurance pene	tration	
	(6)	(7)	(8)	(9)	(10)
Lagged dependent variable	es 0.503** (2.237)	0.503** (9.303)	0.554** (7.007)	0.559** (4.946)	0.503** (4.486)
Epidemic (death)	(2.237) 0.943×10^{-1} (5.612)		(1.007)	(1.940)	(4.400)
Flood (death)	(0.012)	-0.920×10 (0.925)	—7		
Climatological (death)			0.133×10 (4.220)) ⁻⁶ **	
Earthquake (death)				0.19×10 (1.617)) ⁻⁷
Windstorm (death)				()	0.43×10^{-6} (0.624)
Real GDP	0.001** (2.197)	0.002** (2.078)	0.002** (3.045)	0.002* (1.827)	0.002 (1.361)
Inflation rate		** -0.001**			$(1.501)^{-3} -0.001^{**}$ (-3.044)
Interest rate	-0.863×10^{-129}	$(-4.535)^{4}$ -0.37×10^{-10}	$(-2.203)^{3**} -0.38 \times 10^{-1}$	-3** -0.001**	(-3.044) -0.001^{**}

Table 4 GMM regression estimates: Insurance penetration

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		Life insurance penetration						
	(6)	(7)	(8)	(9)	(10)			
	(-0.714)	(-2.480)	(-2.407)	(-2.265)	(-3.010)			
Health expenditure	-0.003 **	-0.002*	-0.002**		$0^{-3} - 0.003$			
	(-2.562)	(-1.710)	(-2.812)	(0.092)	(-1.075)			
Dependency ratio	-0.003*	-0.005*	-0.005	-0.012*	-0.015 **			
	(-1.936)	(-1.959)	(-1.570)	(-1.785)	(-6.611)			
Arellano-Bond test (1)	0.001	0.001	0.001	0.002	0.000			
Arellano-Bond test (2)	0.434	0.232	0.323	0.377	0.339			
Hansen test	0.192	0.195	0.245	0.196	0.224			
		Non-lij	^f e insurance pene	etration				
	(11)	(12)	(13)	(14)	(15)			
Lagged dependent	0.582**	0.583**	0.586**	0.597**	0.501**			
variables	(6.819)	(8.401)	(7.468)	(7.602)	(4.343)			
Epidemic (death)	0.209×10^{-6}			()				
-F)	(3.469)							
Flood (death)		0.13×10^{-6}	*					
, , ,		(2.788)						
Climatological (death)		· · ·	0.17×10^{-6} *	*				
8 ()			(2.413)					
Earthquake (death)			· · · ·	0.493×10^{-1}	-8			
···· 1···· (·····)				(0.624)				
Windstorm (death)				(0.01)	$0.47 \times 10^{-6**}$			
					(2.102)			
Real GDP	0.001**	0.001**	0.001*	0.001**	0.001**			
	(2.065)	(2.850)	(1.901)	(3.594)	(2.298)			
Inflation rate	-0.21×10^{-3} **			· · · ·	$^{-4} - 0.051 \times 10^{-4}$			
initiation face	(-2.709)	(-1.039)	(-1.509)	(-0.155)	(-0.707)			
Interest rate	0.774×10^{-4}	0.184×10^{-3}	()	((
Interest fate	(1.095)	(1.030)	(0.731)	(-1.720)	(0.790)			
Health expenditure	-0.001**	-0.001^{**}	-0.003**	(-1.720) -0.002^{**}	-0.002**			
ricann expenditure	(-2.688)	(-3.553)	(-3.589)	(-3.566)	(-2.324)			
Dependency ratio	(-2.088) -0.004^{**}	(-3.333) -0.004**	(-3.389) -0.005*	(-3.300) -0.005**	(-2.324) -0.003			
Dependency failo	(-2.307)	(-2.779)	(-1.881)	(-2.062)	(-1.477)			
Arellano–Bond test (1)	0.001	0.000	0.001	0.000	0.001			
Arellano–Bond test (1) Arellano–Bond test (2)	0.211	0.000	0.333	0.234	0.325			
Hansen test	0.137	0.264	0.229	0.365	0.149			

Table 4 (continued)

Notes: The natural disaster variables correspond to deaths caused by natural disasters. The regressions include a constant term. The *t*-values are in parentheses. ****** and ***** indicate the statistical significance at the 5 per cent and 10 per cent levels, respectively.

who show that aggregate income contributes to higher non-life insurance consumption.

As anticipated, we find that the variable inflation rate is negative and statistically significant in most specifications at least at the 10 per cent level, suggesting that higher rates of inflation reduce total insurance consumption, as well as life insurance and non-life insurance consumption. These findings are in line with Browne and Kim,⁵⁷

Outreville,⁴⁸ Ward and Zurbruegg,⁴⁹ Beck and Webb,⁵² Li *et al.*,⁴⁶ and Feyen *et al.*,⁴⁵ who discover that a rise in the inflation rate lowers life insurance consumption. Overall, our results also indicate that higher interest rates contribute to a decrease in life insurance and non-life insurance consumption. These findings are in line with Li *et al.*,⁴⁶ who find that greater interest rates are associated with lower life insurance consumption. However, these results are not consistent with Beck and Webb,⁵² who show that countries with higher interest rates experience life insurance market development.⁹²

In general, our results provide mixed findings on the relationship between health expenditures and insurance market development. In Table 1, for example, we find evidence that higher health expenditures are associated with lower life insurance density (columns 6–10), while higher health expenditures contribute to greater non-life insurance density (columns 11–15). Furthermore, this effect is statistically insignificant at conventional levels in the total insurance density model (columns 1–5) in Table 1. In addition, our findings overall suggest that higher health expenditures are associated with higher insurance penetration in Table 2. Nevertheless, we provide evidence that the variable health expenditure is positive and statistically significant at conventional levels in Tables 3 and 4. Overall, we find no robust relationship between government health expenditures and total insurance market development, including life insurance and non-life insurance consumption.

The literature also finds that the relationship between government expenditures on social welfare and insurance market development is rather uncertain. Browne and Kim⁵⁷ find that government spending on social welfare leads to higher life insurance consumption. However, Beenstock *et al.*,⁸⁷ Ward and Zurbruegg,⁴⁹ Li *et al.*,⁴⁶ and Feyen *et al.*⁴⁵ show that higher government provisions on social welfare reduce life insurance consumption. Furthermore, Outreville,⁴⁸ Beck and Webb,⁵² and Hwang and Greenford⁹⁰ discover that public provision on social welfare has a statistically insignificant impact on life insurance market development. Since these studies generally employ different measures of government spending on social welfare and often utilise diverse sets of countries in the empirical analysis, it is perhaps not surprising that the literature finds no robust link between public expenditures on social welfare and insurance consumption.⁴⁵

Finally, the variable dependency ratio has a statistically insignificant impact on total insurance consumption in most equations in Tables 1–4. Alternatively, this effect is negative and statistically significant at least at the 10 per cent level in most equations for the life insurance and non-insurance models in Tables 1–4, thereby providing evidence that a higher dependency ratio causes a decline in insurance consumption. These results are not consistent with the theoretical work of Campbell⁹³ and the empirical works of Hammond *et al.*,⁶⁰ Beenstock *et al.*,⁸⁷ Truett and Truett,⁸⁸ Browne and Kim,⁵⁷ Hwang and Greenford,⁹⁰ Li *et al.*,⁴⁶ and Feyen *et al.*,⁴⁵ who show that a

93 Campbell (1980).

⁹² As can be seen, we also find evidence that higher interest rates have a statistically insignificant influence on insurance market development. It is also important to note that Outreville (1996) finds interest rates have a statistically insignificant impact on life insurance market development.

greater dependency ratio is associated with higher life insurance market development.⁹⁴ Nevertheless, our results are in line with those of Ward and Zurbruegg,⁴⁹ who discover that an increase in the young dependency ratio contributes to lower life insurance consumption in a sample of 16 Asian countries.⁹⁵

We provide the results of Hansen and Arellano–Bond tests at the bottom of each table. The Hansen test of over-identification restrictions tests the validity of the instruments (amounting to a test for the exogeneity of the covariates). As can be seen, the Hansen test cannot reject the null hypothesis (p-value > 0.10) in all equations, suggesting that the instrumental variables are valid in the estimation. Next, the Arellano–Bond tests of first-order autocorrelation and second-order autocorrelation tests that the estimated residuals do not produce first-order and second-order serial correlation, respectively. While autocorrelation of the first-order prevails by definition, second-order autocorrelation must be absent in order for the estimator to be consistent. The Arellano–Bond test of second-order autocorrelation cannot reject the null hypothesis (p-value > 0.10) in all equations, indicating that the estimated residuals do not produce second-order serial correlation and, thus, the estimators are consistent in all specifications.

Extended specification

In the extended model, we estimate whether the political risk level of a country impacts insurance market development. In addition, we examine the interaction effects of natural disaster variables and the political risk level of a country on insurance consumption. We provide the regression estimates for the dependent variables' total insurance density (columns 1–5), life insurance density (columns 6–10) and non-life insurance density (columns 11–15) in Table 5, whereas the regression estimates for the dependent variables' total insurance penetration (columns 6–10) and non-life insurance penetration (columns 6–10) and non-life insurance penetration (columns 6–10) and non-life insurance penetration (columns 11–15) are presented in Table 6. In Tables 5 and 6, the natural disaster variables are the number of natural disasters, specifically epidemic, flood, climatological disasters, earthquake and windstorm that occurred. As before, we employ a two-step system GMM model in the empirical analysis.

To start, we find that epidemic, flood, windstorm and climatological disasters are associated with higher total insurance density at least at the 10 per cent level of statistical significance in Table 5. Also, it appears that all five natural disaster variables contribute to larger life insurance density, at the 5 per cent level of statistical significance. These effects are also similar in the non-life insurance density model, except for the natural disaster variable flood (column 12) in Table 5, which is statistically insignificant at conventional levels. Also, we find that the natural disaster variables epidemic, flood, climatological disasters and windstorm are significantly

⁹⁴ Moreover, Outreville (1996), and Beck and Webb (2003) find that the young dependency ratio has a statistically insignificant impact on life insurance consumption. However, Beck and Webb (2003) also show that a rise in the old dependency ratio leads to higher life insurance consumption.

⁹⁵ It is important to note that Ward and Zurbruegg (2002) also find that higher young dependency ratio is associated with higher life insurance consumption in a sample of 25 OECD countries.

	Total insurance density					
	(1)	(2)	(3)	(4)	(5)	
Lagged dependent variables	0.559**	0.555**	0.514**	0.561**	0.527**	
Epidemic (number)	(6.287) 0.160** (4.693)	(3.469)	(2.990)	(3.657)	(2.917)	
Flood (number)	(4.093)	0.191* (1.832)				
Climatological (number)		(1.052)	1.085** (2.402)			
Earthquake (number)				0.160 (0.458)		
Windstorm (number)				~ /	0.122** (2.480)	
Risk	0.108 (0.978)	0.294** (2.553)	0.177** (3.100)	0.016** (2.115)	0.165 (0.990)	
Epidemic × risk	0.042** (2.759)					
Flood × risk		0.043* (1.698)				
Climatological × risk			0.257** (2.480)			
Earthquake × risk				0.037** (3.439)		
Windstorm \times risk					0.032** (2.543)	
Real GDP	0.022 (0.473)	0.052 (0.588)	0.140* (1.756)	0.045 (0.631)	0.091 (1.271)	
Inflation rate	-0.043^{**} (-4.576)	-0.043^{**} (-2.581)	-0.036^{**} (-2.781)	-0.044^{**} (-3.463)	-0.040^{**} (-3.227)	
Interest rate	-0.031^{**} (-3.162)	-0.028^{**} (-1.976)	-0.035^{**} (-1.960)	-0.036^{**} (-2.947)	-0.029^{**} (-2.069)	
Health expenditure	0.072 (0.978)	0.022 (0.150)	0.056 (0.718)	0.017 (0.191)	0.053 (0.630)	
Dependency ratio	-0.093 (-0.520)	-0.102 (-0.453)	-0.140 (-0.798)	-0.026 (-0.136)	-0.118 (-0.436)	
Arellano–Bond test (1)	0.001	0.001	0.000	0.000	0.001	
Arellano–Bond test (2)	0.211	0.220	0.434	0.322	0.213	
Hansen test	0.113	0.150	0.104	0.107	0.108	
		Lif	e insurance dens	ity		
	(6)	(7)	(8)	(9)	(10)	
Lagged dependent variables	0.551** (7.264)	0.542** (3.363)	0.549** (5.872)	0.551** (4.349)	0.550** (6.940)	
Epidemic (number)	1.499** (48.590)					
Flood (number)	(10.390)	1.188** (22.281)				

 Table 5
 GMM regression estimates: Insurance density

		Life	e insurance densi	ty	
	(6)	(7)	(8)	(9)	(10)
Climatological (number)			6.922**		
			(21.402)		
Earthquake (number)			· · ·	1.029**	
• • · · ·				(2.823)	
Windstorm (number)				× /	2.684**
× ,					(9.645)
Risk	1.133**	3.821**	1.053**	1.807**	1.823**
	(5.285)	(13.070)	(4.564)	(8.370)	(4.130)
Epidemic × risk	3.616**	· · · · ·			. ,
L.	(61.553)				
Flood \times risk	· · · ·	2.822**			
		(23.129)			
Climatological × risk		(1.670**		
			(23.368)		
Farthquake × risk			(20.000)	2 487**	

Table 5

		(23.308)		
			2.487**	
			(3.025)	
				66.058**
				(10.592)
2.794**	3.035**	2.853**	2.932**	2.818**
(21.610)	(9.158)	(19.755)	(11.073)	(16.264)
-17.613 **	-23.013 **	-13.012**	-9.111 **	-11.149**
(-23.322)	(-20.443)	(-22.309)	(-10.050)	(-12.215)
-43.838 **	-36.342**	-50.033 **	-49.046**	-49.375 **
(-12.681)	(-9.049)	(-32.976)	(-14.336)	(-31.719)
-6.246**	-1.048**	-1.062**	-9.100 **	-9.473 * *
(-8.491)	(-9.753)	(-8.599)	(-11.839)	(-4.608)
-8.471 **	-1.038**	-1.021**	-9.880**	-9.925**
(-12.924)	(-9.782)	(-36.404)	(-19.535)	(-20.824)
0.001	0.002	0.001	0.000	0.000
0.432	0.341	0.341	0.432	0.333
0.107	0.130	0.123	0.325	0.394
	$\begin{array}{c} (21.610) \\ -17.613^{**} \\ (-23.322) \\ -43.838^{**} \\ (-12.681) \\ -6.246^{**} \\ (-8.491) \\ -8.471^{**} \\ (-12.924) \\ 0.001 \\ 0.432 \end{array}$	$\begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

	Non-life insurance density					
	(11)	(12)	(13)	(14)	(15)	
Lagged dependent variables	0.503** (3.520)	0.594* (7.615)	0.599** (5.225)	0.501** (2.945)	0.506** (3.147)	
Epidemic (number)	1.490** (5.704)					
Flood (number)	. ,	0.800 (1.033)				
Climatological (number)			5.753** (3.528)			
Earthquake (number)				4.451** (3.539)		
Windstorm (number)				(0.000)	5.751** (3.780)	
Risk	5.183** (8.989)	8.420* (1.915)	4.506** (6.196)	5.767** (5.940)	6.025** (4.920)	

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Table 5	(continued))
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	Non-life insurance density						
	(11)	(12)	(13)	(14)	(15)		
Epidemic × risk	3.337** (6.478)						
$Flood \times risk$		1.845 (1.209)					
$Climatological \times risk$			1.494* (1.668)				
Earthquake \times risk			()	1.678* (1.656)			
Windstorm \times risk				(1.000)	3.101** (3.710)		
Real GDP	5.946* (1.750)	17.806 (1.484)	1.793 (0.511)	7.296** (3.205)	(3.439)		
Inflation rate	-6.421**	-6.331**	()	-7.404**	-7.072**		
Interest rate	(-11.123) -22.509** (-22.571)	-26.217**	(-29.879) -24.302^{**} (-28.989)	-23.940**	-22.481**		
Health expenditure	-57.831**	-60.561**	-55.433**	-61.067**	-64.470**		
Dependency ratio	(-38.424) -1.564** (-2.232)	(-2.747) -1.347 (-0.774)	(-17.804) -0.719* (-1.799)	(-13.604) 0.959 (0.542)	(-17.035) -1.406* (-1.817)		
Arellano–Bond test (1) Arellano–Bond test (2)	0.001 0.199	0.001 0.103	0.002 0.223	0.000 0.436	0.001 0.231		
Hansen test	0.254	0.241	0.207	0.228	0.213		

Notes: The natural disaster variables correspond to the incidences (number) of natural disasters that occurred. The regressions include a constant term. The *t*-values are in parentheses. ****** and ***** indicate the statistical significance at the 5 per cent and 10 per cent levels, respectively.

associated with higher total insurance penetration and non-life insurance penetration, while only a rise in the number of epidemic, flood, earthquake and climatological disasters stimulate the demand for life insurance penetration (Table 6). As such, our findings suggest that the occurrence (number) of natural disasters contribute to the development of insurance markets.

Moreover, we investigate whether deaths attributable to these five natural disaster variables impact the demand for total insurance, as well as life insurance and non-life insurance. The GMM regression estimates for the dependent variables' total insurance density (columns 1–5), life insurance density (columns 6–10) and non-life insurance density (columns 11–15) are presented in Table 7, while the GMM regression estimates for the dependent variables' total insurance penetration (columns 6–10) and non-life insurance penetration (columns 6–10) and non-life insurance penetration (columns 6–10) and non-life insurance penetration (columns 11–15) are displayed in Table 8. We provide evidence that deaths attributable to epidemic, climatological disasters and windstorm significantly promote total insurance density. Also, we find that deaths caused by epidemic, flood, climatological disasters and windstorm increases life insurance density, whereas deaths caused only by climatological disasters and windstorm contributes to higher non-life insurance density (Table 7).

		Total insurance penetration						
	(1)	(2)	(3)	(4)	(5)			
Lagged dependent variables	0.655**	0.672**	0.655**	0.625**	0.675**			
Epidemic (number)	(3.360) 0.017** (3.602)	(3.931)	(5.243)	(8.102)	(3.143)			
Flood (number)	(3.002)	0.015** (2.777)						
Climatological (number)		(2.777)	0.013* (1.648)					
Earthquake (number)			(1.040)	0.015 (0.657)				
Windstorm (number)				(0.057)	0.012** (3.079)			
Risk	0.005**	0.012	0.009^{**}	0.007	0.010**			
Epidemic × risk	(2.690) 0.004**	(1.574)	(2.989)	(1.158)	(2.461)			
$Flood \times risk$	(3.672)	0.003**						
Climatological \times risk		(2.776)	0.003*					
Earthquake \times risk			(1.802)	0.004				
Windstorm \times risk				(0.638)	0.003**			
Real GDP	0.003	0.002	0.002	0.004*	(2.073) 0.002			
Inflation rate	$(1.152) \\ 0.406 \times 10^{-3}$				(0.767) 0.001			
Interest rate			(0.153) -0.015×10^{-3}		(1.638) 0.503×10^{-4}			
Health expenditure	(-0.304) -0.002	(-0.668) -0.002	-0.044×10^{-2}		(0.172) -0.002			
Dependency ratio	(-0.843) 0.347×10^{-3} (0.030)	(-0.776) -0.006 (-0.783)	-0.002	(-0.660) -0.003 (-0.330)	(-0.639) 0.001 (0.101)			
Arellano–Bond test (1)	0.001	0.000	0.001	0.002	0.001			
Arellano-Bond test (2)	0.321	0.345	0.399	0.433	0.436			
Hansen test	0.326	0.254	0.509	0.228	0.273			
		Life	insurance penetr	ation				
	(6)	(7)	(8)	(9)	(10)			
Lagged dependent variables	0.668** (5.754)	0.615** (3.860)	0.669** (6.728)	0.689** (2.249)	0.684** (5.682)			
Epidemic (number)	0.022* (1.729)	(2.000)	(,=0)	(>)	(2.002)			
Flood (number)	(1.727)	0.008* (1.809)						

 Table 6
 GMM regression estimates: Insurance penetration

Table 6 (continued)

	Life insurance penetration								
	(6)		(7)		(8)		(9)		(10)
Climatological (number	·)				0.030**	k			
Earthquake (number)					(4.173)		0.020**		
Windstorm (number)							(2.126)		0.003
Risk	0.023**		0.007		0.022**	k	0.010		(0.386) 0.019**
Epidemic × risk	(4.047) 0.006* (1.806)		(1.510)		(3.191)		(1.121)		(2.728)
$Flood \times risk$	(11000)		0.002* (1.853)						
Climatological \times risk			()		0.007** (4.323)	k			
Earthquake \times risk					(0.005** (2.150)		
Windstorm \times risk							(2.150)		0.001 (0.442)
Real GDP	$-0.045 \times$ (-0.274)	10^{-3}	0.001 (1.190)		0.002 (0.690)		$-0.130 \times (-0.051)$	10^{-3}	0.001 (0.293)
Inflation rate	(-0.274) $-0.379 \times$ (-1.748)		(-0.001^{*}) (-3.574)	k	0.183 × (0.536)		(-0.051) 0.141 × (0.479)	10^{-3}	0.001 (1.316)
Interest rate	$(-0.003 \times (-0.855))$		0.339 × (1.332)	× 10 ⁻³	(0.550) -0.001 (-1.452)		(0.479) -0.001** (-2.530)		(1.510) -0.001* (-1.756)
Health expenditure	-0.003 (-0.915)		(-0.004^{*}) (-2.686)	k	(-1.452) -0.005 (-1.377)		(-0.003) (-0.860)		-0.004 (-0.834)
Dependency ratio	-0.010^{*} (1.926)	,	0.002 (0.499)		0.007 (0.967)		(-0.021^{**}) (-3.141)		0.011 (1.394)
Arellano–Bond test (1) Arellano–Bond test (2)	0.002		0.001		0.001 0.454		0.000 0.412		0.001 0.422
Hansen test	0.270		0.318		0.434		0.218		0.199
_			Non-lij	fe insu	rance pene	tration			
	(11)	(1	2)	(13)	(14)		(15)
Lagged dependent variables Epidemic (number)	0.611** (7.802) 0.010** (6.604)	0.620 (2.458		0.655 (3.873		0.691 (4.096		0.69 (3.61	
Flood (number)	(0.004)	0.006 (2.041							
Climatological (number) Earthquake (number)		(2.04)		0.433 (2.150	8 × 10 ⁻³ **	0.005			
Windstorm (number)						(1.246		0.00 (4.67	

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	Non-life insurance penetration							
	(11)	(12)	(13)	(14)	(15)			
Risk	-0.001 (-0.337)	0.004 (1.356)	0.159×10^{-3} (0.156)	0.002** (3.041)	0.002** (3.281)			
Epidemic \times risk	0.003** (6.867)	(1.550)	(01120)	(01011)	(0.201)			
$Flood \times risk$		0.001** (2.071)						
$Climatological \times risk$			0.211×10^{-3} * (3.316)	*				
Earthquake \times risk				0.001 (1.318)				
Windstorm \times risk					$0.379 \times 10^{-3**}$ (3.675)			
Real GDP		-0.088×10^{-3} (-0.126)	0.001** (2.055)	0.002** (2.320)	0.001* (1.713)			
Inflation rate	-0.374×10^{-4} (-0.369)	-0.811×10^{-4}	(-0.131×10^{-3}) (-1.085)		0.843×10^{-4} (0.600)			
Interest rate		(-1.097) * (-0.213×10^{-3})	0.643×10^{-4} (0.540)	$-0.305 \times 10^{-3**}$ (-2.601)	0.186×10^{-3} (1.340)			
Health expenditure	0.003** (2.830)	0.001 (0.910)	0.003** (2.671)	0.003** (2.715)	0.001 (1.455)			
Dependency ratio	-0.007^{**} (-1.997)	-0.003 (-1.258)	-0.007** (-1.987)	-0.007^{**} (-2.041)	-0.003 (-1.144)			
Arellano-Bond test (1	1) 0.000	0.001	0.001	0.001	0.002			
Arellano-Bond test (2	· · · · · · · · · · · · · · · · · · ·	0.223	0.255	0.212	0.299			
Hansen test	0.353	0.269	0.105	0.069	0.111			

Table 6 (continued)

Notes: The natural disaster variables correspond to the incidences (number) of natural disasters that occurred. The regressions include a constant term. The *t*-values are in parentheses. ****** and ***** indicate the statistical significance at the 5 per cent and 10 per cent levels, respectively.

Furthermore, our findings suggest that deaths attributable to epidemic, climatological disasters and windstorm are significantly associated with higher total insurance penetration (Table 8). Also, it appears that deaths caused only by flood and windstorm lead to greater life insurance penetration, while deaths attributable to only floods cause an increase in non-life insurance penetration (Table 8). Overall, we provide robust evidence that the incidences of natural disasters and natural disaster deaths persuade individuals to invest in necessary protective measures, that is, purchasing life insurance and non-life insurance products. Nevertheless, we discover that not all natural disaster variables stimulate the demand for life insurance and non-life insurance policies. Since these natural disasters are associated with different scales of economic and human losses, it is perhaps not surprising that not all natural disasters induce residents to purchase insurance to secure financial protection.

Overall, we find that the variable risk is positive and statistically significant at the 5 per cent level in most specifications in the total insurance density models (columns 1-5) in Tables 5 and 7. This effect is also positive and statistically significant at

	Total insurance density					
	(1)	(2)	(3)		(4)	(5)
Lagged dependent variables	0.558** (4.160)	0.514** (3.035)	0.653** (3.639)	0.55 (4.76		0.652** (4.568)
Epidemic (death)	0.003** (3.966)	(5.055)	(5.657)	(1.70	,)	(1.500)
Flood (death)	(0.0.00)	-0.002 (-0.907)				
Climatological (death)		(0.135×1 (3.159)	0^{-3} **		
Earthquake (death)			()	-0.10 (-0.51	5×10^{-3} 5)	
Windstorm (death)					,	0.001** (3.217)
Risk	0.253**	0.129**		0.05		0.043
Epidemic × risk	(2.255) 0.001 (0.983)	(0.815)	(0.585)	(0.54	7)	(0.424)
$Flood \times risk$	(0.965)	0.001** (3.905)				
Climatological \times risk		(0.000)	0.345×1 (3.177)	0^{-4**}		
Earthquake \times risk				0.27 (2.51	0×10^{-4}	
Windstorm \times risk				(2.51	0)	0.217×10^{-3} (1.222)
Real GDP	0.013	0.002	0.073	0.05		0.077
Inflation rate	(0.203) -0.033^{**}	(0.028) -0.043**		(0.80 - 0.03)	8**	(1.033) -0.043**
Interest rate	(-2.432) -0.028*	(-4.811) -0.033^{**}		(-3.86) -0.03	18*	(-4.514) -0.035** (-4.484)
Health expenditure	(-1.870) 0.080 (0.815)	(-3.124) 0.145 (1.196)	(-3.183) 0.017 (0.231)	(-2.16 0.01 (0.09	0	(-4.484) -0.018 (-0.153)
Dependency ratio	-0.204	-0.162	-0.177	-0.09	5	-0.020
Arellano-Bond test (1)	(-1.038) 0.000	(-0.851) 0.001	(-0.893) 0.001	(-0.51) 0.00	/	(-0.128) 0.001
Arellano–Bond test (2) Hansen test	0.143 0.108	0.199 0.106	0.334 0.116	0.34 0.10		0.223 0.102
				nsurance density		
	(6)		(7)	(8)	(9)	(10)
Lagged dependent variables	0.55		0.557** (4.372)	0.655** (8.619)	0.650** (5.189)	0.593** (7.593)
Epidemic (death)	17.39	7**		(0.017)	(3.10))	(1.555)
Flood (death)	(7.00	1	0.047** 8.429)			
Climatological (death)		(1	0.427)	0.492* (1.743)		

Table 7 GMM regression estimates: Insurance density

	Life insurance density						
	(6)	(7)	(8)	(9)	(10)		
Earthquake (death)				0.164			
W7 1 ((1 (1)				(0.571)	2 405**		
Windstorm (death)					2.405**		
Risk	1.027**	1.056**	1.632**	1.802**	(6.033) 3.119**		
KISK	(4.298)	(4.046)	(3.824)	(5.494)	(29.330)		
Epidemic \times risk	4.207**	(4.040)	(3.824)	(3.494)	(29.330)		
Lpideinie × lisk	(7.984)						
$Flood \times risk$	(7.501)	2.439**					
		(18.443)					
Climatological × risk		× /	0.114				
e			(1.467)				
Earthquake × risk			. ,	0.041			
				(0.562)			
Windstorm \times risk					0.587**		
					(6.506)		
Real GDP	2.694**	2.381**	2.786**	3.140**	24.752*		
	(23.656)	(11.152)	(29.028)	(33.988)	(1.643)		
Inflation rate	-13.490 **	-16.461**	-12.381**	-10.466 **	-7.251**		
_	(-33.387)	(-13.099)	(-8.924)	(-18.637)	(-7.204)		
Interest rate	-45.904**	-45.862**	-42.390**	-43.798**	-43.205**		
** 1.1 1.	(-37.446)	(-24.853)	((-26.509)	(-38.047)		
Health expenditure		-94.433**					
D. I. st	(-7.954) -1.018**	(-7.106)	(-5.779) -8.655**	(-7.263)	(-2.677) -1.836**		
Dependency ratio		-8.480**		-1.014**			
Anallana Dand tast (1)	(-22.661) 0.001	(-17.188) 0.000	(-50.368) 0.001	(-20.033) 0.001	(-7.327) 0.002		
Arellano–Bond test (1) Arellano–Bond test (2)	0.001	0.000	0.001	0.001	0.002		
Hansen test	0.102	0.309	0.300	0.367	0.342		
manoen test	0.102	0.500	0.004	0.157	0.105		

Table 7 (continued)

	Non-life insurance density						
	(11)	(12)	(13)	(14)	(15)		
Lagged dependent variables	0.554** (3.306)	0.594** (2.754)	1.001** (2.955)	0.502** (5.228)	0.598** (3.757)		
Epidemic (death)	1.526 (1.541)				()		
Flood (death)		0.247 (1.241)					
Climatological (death)			1.515** (7.935)				
Earthquake (death)				-0.277 (-1.229)			
Windstorm (death)					1.538** (5.579)		
Risk	68.576** (3.479)	70.017** (3.111)	50.154** (4.132)	76.857** (8.024)	70.024** (5.454)		

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	Non-life insurance density						
	(11)	(12)	(13)	(14)	(15)		
Epidemic × risk	0.388*						
-	(1.645)						
$Flood \times risk$		0.001**					
		(41.814)					
Climatological × risk			0.348**				
-			(8.021)				
Earthquake × risk				0.072			
-				(1.259)			
Windstorm × risk					0.367**		
					(5.851)		
Real GDP	2.803	0.752	0.306	4.143	0.544		
	(1.454)	(0.599)	(0.045)	(1.317)	(0.145)		
Inflation rate	-6.953 **	-7.157**	-6.388**	-5.718**	-5.670 **		
	(-10.249)	(-41.884)	(-19.981)	(-5.475)	(-19.086)		
Interest rate	-22.912**	-24.668 **	-19.636**	-21.793 **	-23.936**		
	(-30.349)	(-27.451)	(-23.242)	(-18.278)	(-35.010)		
Health expenditure	-62.075 **	-56.921**	-53.266**	-67.279 **	-55.862**		
	(-20.513)	(-12.748)	(-20.573)	(-21.279)	(-15.891)		
Dependency ratio	-85.773**	-1.748**	-16.751	-45.445*	-1.006*		
	(-3.163)	(-4.220)	(-0.486)	(-1.710)	(-1.841)		
Arellano-Bond test (1)	0.001	0.001	0.000	0.001	0.001		
Arellano–Bond test (2)	0.332	0.255	0.544	0.226	0.221		
Hansen test	0.129	0.086	0.124	0.133	0.205		

Notes: The natural disaster variables correspond to deaths caused by natural disasters. The regressions include a constant term. The *t*-values are in parentheses. ****** and ***** indicate the statistical significance at the 5 per cent and 10 per cent levels, respectively.

conventional levels in all specifications in the life insurance density (columns 6–10) and non-life insurance density (columns 11–15) models in Tables 5 and 7. In general, we also find evidence that the political risk level of a country significantly impacts life insurance, non-life insurance and total insurance penetration (Tables 6 and 8). Hence, our results suggest that countries with lower levels of political risk experience greater insurance consumption. Our results are generally consistent with Ward and Zurbruegg,⁴⁹ and Feyen *et al.*,⁴⁵ who show that countries with a higher quality legal environment experience life insurance market development. These findings are also broadly in line with Esho *et al.*⁶³ and Feyen *et al.*,⁴⁵ who find that enforcement of legal rights contributes to higher non-life insurance consumption.⁹⁶

As such, our results provide strong evidence that the political environment is an important determinant of insurance consumption across countries. More specifically,

⁹⁶ Also, Browne *et al.* (2000) find that the legal system is a significant determinant of non-life insurance development: OECD countries with common-law systems as compared to statutory-law systems experience higher motor vehicle and general liability insurance consumption.

	Total insurance penetration					
	(1)	(2)	(3)	(4)	(5)	
Lagged dependent variables		0.556**	0.545**	0.516**	0.535**	
Epidemic (death)	$(4.479) \\ 0.24 \times 10^{-3} *$	(8.626)	(3.530)	(3.036)	(3.702)	
Flood (death)	(1.700)	0.216×10^{-4} (0.211)				
Climatological (death)		(0.211)	0.75×10^{-4} (1.737)	*		
Earthquake (death)			(1.757)	0.175×10^{-4} (1.094)	1	
Windstorm (death)				(1.074)	$0.69 \times 10^{-4**}$ (3.780)	
Risk	0.005	0.003**	0.014**	0.008	0.008**	
Epidemic × risk	(0.946) $0.60 \times 10^{-4}*$ (1.728)	(2.560)	(1.958)	(1.384)	(3.167)	
Flood × risk	(1.726)	$0.52 \times 10^{-5*3}$ (4.211)	*			
Climatological \times risk		(0.17×10^{-4} (1.741)	*		
Earthquake \times risk			(11711)	0.041×10^{-1} (1.094)	5	
Windstorm \times risk				(1105.1)	0.17×10^{-4}	
Real GDP	0.004	0.004	0.001	0.004	(3.844) 0.003	
Inflation rate	(1.509) 0.001	(1.473) -0.001*	(0.548) -0.001*	(1.537) -0.44×10^{-3}	(1.353) 0.451×10^{-3}	
Interest rate	$(1.254) \\ 0.233 \times 10^{-3}$		(-1.668) -0.316×10^{-1}		(1.445) ³ -0.758 × 10 ⁻⁴	
Health expenditure	(0.644) -0.003	(0.229) -0.004**	(-0.094) 0.001	(0.440) -0.005	(-0.264) -0.003	
Dependency ratio	(-0.798) -0.003 (-0.476)	(-1.971) -0.004	(0.200) -0.005 (-0.(40))	(-1.133) -0.005 (-0.640)	(-1.252) -0.002 (-0.207)	
Arellano–Bond test (1)	(-0.476) 0.002	(-0.590) 0.000	(-0.649) 0.001	(-0.640) 0.001	(-0.307) 0.002	
Arellano-Bond test (2)	0.431	0.332	0.377	0.313	0.342	
Hansen test	0.439	0.330	0.474	0.364	0.338	
		Life	insurance penet	ration		
	(6)	(7)	(8)	(9)	(10)	
Lagged dependent variables	0.584** (9.826)	0.588** (8.326)	0.587** (9.149)	0.599** (9.785)	0.590** (4.409)	
Epidemic (death)	(0.81×10^{-4}) (0.599)	(0.020)	(2.1.12)	().(0)	(1.10)	
Flood (death)	(0.577)	$0.12 \times 10^{-3**}$ (2.198)				
Climatological (death)		(2.190)	0.153×10^{-4} (0.373)			

 Table 8
 GMM regression estimates: Insurance penetration

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Table 8 (continued)

	Life insurance penetration						
	(6)	(7)	(8)	(9)	(10)		
Earthquake (death)				-0.441×10^{-5} (-0.474)			
Windstorm (death)				()	$0.73 \times 10^{-4**}$ (3.682)		
Risk	0.022** (3.036)	0.023** (3.775)	0.017** (2.421)	0.013** (2.213)	0.022** (3.896)		
Epidemic \times risk	0.19×10^{-4} (0.594)		()	()	(0.000)		
$Flood \times risk$	(0.03.1)	0.30×10^{-4} * (2.203)	*				
$Climatological \times risk$		(2.203)	$0.34 \times 10^{-5*}$ (3.364)	k			
Earthquake \times risk			(5.504)	$0.11 \times 10^{-5*}$ (5.462)	k		
Windstorm \times risk				(3.102)	$0.18 \times 10^{-4**}$ (3.695)		
Real GDP	-0.002 (-0.817)	-0.002 (-0.720)	0.328×10^{-3} (0.098)	0.001 (0.755)	0.003 (1.364)		
Inflation rate	(-0.001) (-1.325)	-0.001^{*} (-1.863)	-0.001^{*} (-1.876)	(0.755) -0.265×10^{-3} (-0.920)			
Interest rate	-0.001* (-1.721)	(-0.283×10^{-3}) (-0.659)	· · · ·	(-0.001^{**}) (-2.384)	(-0.045×10^{-3}) (-1.479)		
Health expenditure	0.001 (0.205)	-0.001 (-0.191)	-0.002 (-0.402)	-0.007^{**} (-2.000)	0.001 (0.372)		
Dependency ratio	-0.015^{**} (-2.018)	0.006 (0.750)	0.006 (0.804)	0.009 (1.171)	0.009 (1.373)		
Arellano–Bond test (1) Arellano–Bond test (2)	0.000 0.365	0.001 0.334	0.001 0.355	0.001 0.366	0.000 0.354		
Hansen test	0.383	0.334	0.333	0.253	0.189		
		Non	e-life insurance pe	enetration			
	(11)	(12)	(13)	(14)	(15)		
Lagged dependent variables	6.429) 0.587**	0.592** (4.346)	0.513** (4.154)	0.521** (5.082)	0.509** (3.255)		
Epidemic (death)	(0.125) 0.384×10 (1.580)		(1.151)	(0.002)	(3.233)		
Flood (death)	(11000)	0.23×10^{-1} (4.371)	-4**				
Climatological (death)		()	0.106×10 (1.118)	0^{-4}			
Earthquake (death)			()	0.49×10^{-6} (0.224)			
Windstorm (death)				()	0.19×10^{-4} ** (2.915)		
Risk	0.001** (2.301)	0.001** (2.363)	0.001** (3.389)	0.003* (1.827)	0.003** (4.204)		

	Non-life insurance penetration				
	(11)	(12)	(13)	(14)	(15)
Epidemic × risk	0.916×10^{-5}				
	(1.550)				
$Flood \times risk$		0.568×10^{-5}			
		(1.379)			
Climatological × risk			0.239×10^{-5}	5	
-			(1.101)		
Earthquake \times risk				0.12×10^{-6}	
-				(0.223)	
Windstorm \times risk					0.47×10^{-5} **
					(3.006)
Real GDP	0.001**	0.002**	0.001	0.40×10^{-3}	0.001**
	(2.268)		(1.377)	(1.020)	(2.188)
Inflation rate	-0.11×10^{-3}	0.546×10^{-4}	-0.95×10^{-4}	0.80×10^{-4}	-0.103×10^{-4}
	(-1.270)	(0.639)	(-0.951)	(0.697)	(-0.108)
Interest rate	0.122×10^{-3}	0.205×10^{-3}		0.77×10^{-4}	0.811×10^{-4}
	(0.883)	(1.714)	(1.261)	(0.486)	(0.624)
Health expenditure	-0.002**	-0.002^{**}	0.002	0.001	0.002
	(-2.566)	(-2.106)	(1.631)	(0.882)	(1.260)
Dependency ratio	-0.007 **	-0.005*	-0.004	0.001	-0.003
	(-2.850)	(-1.838)	(-1.341)	(0.163)	(-0.879)
Arellano-Bond test (1)	0.002	0.001	0.000	0.001	0.001
Arellano–Bond test (2)	0.224	0.298	0.212	0.223	0.230
Hansen test	0.197	0.216	0.039	0.139	0.159

Table 8 (continued)

Notes: The natural disaster variables correspond to deaths caused by natural disasters. The regressions include a constant term. The *t*-values are in parentheses. ****** and ***** indicate the statistical significance at the 5 per cent and 10 per cent levels, respectively.

our findings suggest that countries with lower levels of political risk experience insurance market development. These results are certainly anticipated. For example, La Porta *et al.*⁹⁷ find that the political environment of a country is a significant determinant of capital markets: economies with inferior investor protection are associated with smaller capital markets. Also, Levine⁹⁸ shows that countries with a political environment that promotes "creditor rights" and thoroughly "enforces contracts" experience banking development (p. 1131). Furthermore, Levine⁹⁹ finds that countries with a legal environment that "give a high priority to creditors receiving the full present value of their claims on corporations", "enforce contracts effectively", and "promote comprehensive and accurate financial reporting by corporations" experience financial development (p. 8).

⁹⁷ La Porta *et al.* (1997).

⁹⁸ Levine (1998).

⁹⁹ Levine (1999).

Next, we investigate the interaction effects of our natural disaster variables and political risk. First, we examine whether the incidences of natural disasters impact insurance market development under the tenure of a government with different levels of political risk (Tables 5 and 6). As can be seen, all interaction effects between natural disaster variables and risk are positive and statistically significant at conventional levels in the total insurance density model (columns 1–5) and life insurance density model (columns 6–10) in Table 5. These results suggest that the incidences of natural disasters are associated with higher total insurance density in countries with lower levels of political risk. Furthermore, we provide evidence that the occurrences of epidemic, earthquake, windstorm and climatological disasters also contribute to greater non-life insurance density as the political risk level of a country falls, at least at the 10 per cent level of statistical significance (Table 5).

It appears that the natural disaster variables epidemic, flood, climatological disasters and windstorm also contribute to higher total insurance penetration as the political risk level of a country falls, at least at the 10 per cent level of statistical significance (Table 6). These findings are also the case in the non-life insurance penetration model, at the 5 per cent level of statistical significance (Table 6). Furthermore, the results suggest that an increase in the natural disaster variables epidemic, flood, climatological disasters and earthquake leads to higher life insurance penetration under the tenure of a government with low levels of political risk, at least at the 10 per cent level of statistical significance (column 6-10 in Table 6). In general, we provide evidence that the interaction effects between the incidences (number) of natural disasters and the political risk level of a country is a significant determinant of insurance market development.

Second, we analyse whether deaths caused by these five natural disasters influence the demand for insurance, including life insurance and non-life insurance, in countries with different levels of political risk (Tables 7 and 8). We find that deaths caused by flood, earthquake and climatological disasters lead to higher total insurance density under the tenure of a government with lower levels of political risk, at the 5 per cent level of statistical significance (Table 7). In addition, we discover that deaths attributable to the natural disaster variables epidemic, flood and windstorm contribute to higher life insurance density, whereas deaths caused by epidemic, flood, windstorm and climatological disasters are associated with greater non-life insurance density as the political risk level of a country falls, at least at the 10 per cent level of statistical significance (Table 7).

Finally, we find that deaths attributable to epidemic, flood, windstorm and climatological disasters increase total insurance penetration in countries with lower levels of political risk (Table 8). Also, we show that deaths caused by flood, earthquake, windstorm and climatological disasters lead to higher life insurance penetration under the tenure of a government with low levels of political risk (Table 8). Alternatively, our findings indicate that the interaction effects of our natural disaster variables and political risk have a limited impact on non-life insurance penetration, which is evident by the statistically insignificant coefficients in all equations (columns 11–15) in Table 8. While we show that the interaction effects of natural disaster variables and political risk are important determinants of insurance market development, our findings reveal that not all interaction effects are statistically significant at conventional levels. Nevertheless, we find evidence that the incidences of natural disasters and natural disaster deaths contribute to higher insurance consumption in countries with lower levels of political risk.

In effect, these results imply that the occurrences of natural disasters and deaths caused by natural disasters reduce the demand for insurance, as well as life insurance and non-life insurance, as the political risk level of a country rises. In this context, these findings suggest that a rise in the political risk level of a country mitigates the beneficial effect of natural disaster variables on insurance market development. In summary, we highlight the importance of natural disaster variables, the political risk level of a country and their interaction effects in stimulating total insurance consumption, together with life insurance and non-life insurance consumption. In general, our results are broadly in line with those of Oh and Reuveny,¹⁰ who find that the interaction effects of natural disasters and political risk significantly influence international trade. Also, as can be seen, the impacts of the control variables on insurance market development in the extended model (Tables 5–8) are mostly consistent with our baseline model (Tables 1–4).

Conclusion

We examine the relationship between natural disasters, political risk and insurance market development in a panel of 39 countries over the period 1984–2009 using a dynamic panel two-step system GMM model. We find that natural disasters are important determinants of insurance consumption across countries. In particular, we find that the incidences of natural disasters and deaths caused by natural disasters lead to greater total insurance, as well as life insurance and non-life insurance consumption. Our results therefore provide evidence that the occurrences of natural disasters and deaths attributable to natural disasters influence individuals to invest in appropriate protective measures, that is, purchase insurance policies.

However, we find that not all incidences of natural disasters and natural disaster deaths stimulate the demand for insurance products, including life insurance and nonlife insurance products. Given that floods, earthquakes, windstorms, epidemics and climatological disasters are associated with different scales of economic and human losses, our results that not all natural disasters induce individuals to purchase insurance policies to secure financial protection are perhaps not surprising. Nevertheless, we emphasise that natural disaster variables are important factors in insurance market development, and, therefore, it is imperative to account for these forces in developing and implementing effective insurance policy measures.

We also discover that countries with lower levels of political risk are associated with insurance market development. Furthermore, the incidences of natural disasters and deaths attributable to natural disasters lead to higher insurance consumption under the tenure of a government with lower levels of political risk. In other words, our findings suggest that the occurrences of natural disasters and natural disaster deaths reduce the demand for insurance, as well as life insurance and non-life insurance, as the political risk level of a country rises. Hence, these results indicate that a rise in the political risk level of a country mitigates the beneficial effect of natural disaster variables on insurance market development.

This leads to important policy recommendations, as policymakers and insurance companies need to investigate more closely the causes of political risk across countries to promote the growth of insurance markets. Also, our findings emphasise that governments need to reduce the level of political risk in order to experience insurance market development.¹⁰⁰ Certainly, the political environment of a country influences the investment activities of insurance companies. Therefore, our results suggest that insurance companies need to seek countries with lower levels of political risk to facilitate the demand for insurance products. In summary, our results provide evidence that natural disasters, political risk and their interaction effects are fundamental determinants of insurance consumption across countries.

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- ¹⁰⁰ This is particularly important, as the literature provides strong evidence that insurance market development leads to higher economic growth (see, for example, Lee, 2011).

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Appendix

Variable	Definition	Source	Predicted sign	Mean	Standard deviation	Observations
Total	Total insurance premiums	Swiss Reinsurance		0.058	0.051	1014
insurance penetration	as a percentage of GDP	Company (2011)				
Life insurance	Life insurance premiums as	Swiss Reinsurance		0.035	0.043	1014
penetration	a percentage of GDP	Company (2011)				
Non-life	Non-life insurance	Swiss Reinsurance		0.023	0.013	1014
insurance penetration	premiums as a percentage of GDP	Company (2011)				
Total	(Log) real total insurance	Swiss Reinsurance		983.99	2518.98	1014
insurance density	premiums per capita	Company (2011)				
Life insurance	(Log) real life insurance	Swiss Reinsurance		336.13	25.854	1014
density	premiums per capita	Company (2011)				
Non-life	(Log) real non-life	Swiss Reinsurance		647.86	1052.30	1014
insurance	insurance premiums per	Company (2011)				
density	capita					
Epidemic	The number of epidemic	Emergency Events	+	0.203	0.681	1014
(number)	disasters occurred	Database (2011)				
Flood	The number of floods	Emergency Events	+	1.251	2.129	1014
(number)	occurred	Database (2011)				
Climatological	The number of	Emergency Events	+	0.395	0.873	1014
(number)	climatological disasters occurred	Database (2011)				
Earthquake	The number of earthquakes	Emergency Events	+	0.342	0.920	1014
(number)	occurred	Database (2011)				
Windstorm	The number of windstorms	Emergency Events	+	1.175	2.722	1014
(number)	occurred	Database (2011)				
Epidemic	Deaths caused by epidemic	Emergency Events	+	25.28	221.14	1014
(deaths)	disasters	Database (2011)				
Flood (deaths)	Deaths caused by floods	Emergency Events	+	92.74	976.74	1014
		Database (2011)				
Climatological	Deaths caused by	Emergency Events	+	81.53	1012.03	1014
(deaths)	climatological disasters	Database (2011)				
Earthquake	Deaths caused by	Emergency Events	+	301.41	5371.74	1014
(deaths)	earthquakes	Database (2011)				

Table A1 Data definitions, sources and descriptive statistics

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Table A1	(continued)

Variable	Definition	Source	Predicted sign	Mean	Standard deviation	Observations
Windstorm (deaths)	Deaths caused by windstorms	Emergency Events Database (2011)	+	56.99	431.79	1014
Real GDP	(Log) real GDP per capita (constant 2000 US\$)	World Bank (2011) World Development Indicators	+	9.009	1.337	988
Inflation rate	Annual percentage change in consumer price index	World Bank (2011) World Development Indicators	-	1.418	1.147	961
Interest rate	Lending interest rates	World Bank (2011) World Development Indicators	+/-	1.640	0.781	777
Health expenditures	Health expenditures as a percentage of GDP	World Bank (2011) World Development Indicators	+/-	1.358	0.644	970
Dependency ratio	The ratio of the population under the age of 15 to the population age 15–65	World Bank (2011) World Development Indicators	+/-	4.009	0.200	988
Risk	Political risk index (lower values represent greater political risk)	International Country Risk Guide (2010)	+	4.312	0.1654	1013

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