The Effect of Banking Crises: Evidence from Non-life Insurance Consumption

Shinichi Kamiya, George Zanjani and Jackie Li[1]

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Abstract

We study the connection between banking crises and non-life insurance consumption in 139 countries from 1988 to 2010. After controlling for output, we find a negative excess decline in non-life insurance consumption after the occurrence of a banking crisis only in countries heavily depending on bank credit. The primary contributing factor is motor insurance which loses 113% of the annual premium in the same post-crisis window. The magnitude of premium loss is 60-70% larger in the high income countries. We interpret this finding in the context of the macroeconomic literature on the real effects of banking crises: Reduced consumption of non-life insurance is consistent with a reduction in risk-taking at the societal level that could lead to the persistent post-crisis output effects observed in recent macroeconomic research. We test whether the reduced insurance consumption can be explained by risk-shifting due to the post-crisis contraction of credit and investment.

JEL Codes: G01, G22, E22

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1. Introduction

An interesting and unappreciated consequence of the Great Depression in the United States was a significant retardation in the development of the property–casualty insurance market.[2] As can be seen in Figure 1, the premium volume in relation to gross domestic product (GDP) stagnated for more than 20 years; indeed, at the nadir during the early 1940s, the penetration rate (i.e., the ratio of total

[1] Shinichi Kamiya (Corresponding author): Nanyang Business School, Nanyang Technological University, email: skamiya@ntu.edu.sg; George Zanjani: Department of Risk Management and Insurance, Georgia State University, email: gzanjani@gsu.edu; Jackie Li: Nanyang Business School, Nanyang Technological University, email: JackieLi@ntu.edu.sg. Kamiya acknowledge financial support from the Insurance Risk and Finance Research Centre at Nanyang Business School. The authors are grateful to Michel Dacorogna and Richard Butler for helpful comments.

[2] We use “property-casualty insurance” and “non-life insurance” interchangeably to represent insurance markets other than the life and health insurance markets.

property-casualty insurance premium to GDP) was similar to 1900 levels and was significantly below the levels seen on the eve of the financial crisis in the late 1920s.

Similar outcomes were observed in Scandinavia following the regional banking crises of the early 1990s (see Figure 2), and the same characteristics apply to several countries after the Southeast Asian crisis of the late 1990s (see Figure 3). In all of these cases, the country's economy—measured by per capita GDP—recovered relatively quickly, because the GDP growth rate returned to its pre-crisis level within four years after the financial crisis (Demirguc-Kunt et al., 2006). However, the recovery of non-life insurance consumption lagged significantly, and the industry failed to recuperate its pre-crisis standing in these economies even after a decade or longer.[3]

This paper has two primary objectives. The first is to document that the previous anecdotes are part of a broader pattern. Unlike banking, for which the evidence suggests that aggregate deposits experience little change, even in the short to intermediate term, after a financial crisis (Demirguc-Kunt et al., 2006), we find evidence that non-life insurance consumption tends to decline after a banking crisis only in countries heavily depending on bank credit. Using country-year non-life insurance premium data from 1988 to 2010, we show that the high-credit countries experienced an aggregate 38% loss of annual premiums over 10-year post-crisis window. The premium loss is primarily driven by motor insurance which loses an aggregate 113% of annual premium in the 10-year window. Such significant, negative and persistent effects are not found in property insurance and liability insurance. Moreover, the magnitude of premium decline is 60-70% larger in the high-income countries.[4] Those are excess losses in premium volume that cannot be explained by crisis shock on output level.

This finding dovetails with recent findings in the macroeconomic literature concerning the real effects of financial crises. A growing body of evidence suggests that crises are associated with significant and persistent effects on real output (Cerra and Saxena, 2008; Furceri and Zdzienicka, 2011; Furceri and Mourougane, 2012), but the reasons for these effects are unclear. A variety of mechanisms by which crises might lower potential output have been suggested in the literature (see Furceri and Mourougane, 2012). For instance, banks cut back lending during crisis periods, which may hinder real activity (Dell'Ariccia et al., 2008). Another important line of reasoning focuses on investment channels, arguing that crises raise uncertainty and the risk premiums associated with investment (Pindyck, 1991; Pindyck and Solimano, 1993), perhaps due to their impact on the confidence of investors (Rioja et al., 2011).

[3] In this study, non-life insurance refers to types of insurance other than life insurance and health insurance.
[4] Countries are divided according to the World Bank income group classification. The groups are low-income, lower-middle-income, upper-middle-income, and high-income groups.

To demonstrate the role of bank credit on loss of non-life insurance premium, we sort and partition countries based on the average level of credit over the sample-period, and estimate the impact of a crisis. Figure 4 illustrates the average level of bank private credit during banking crisis periods, and the panel for the high credit countries shows a significant drop of bank private credit by 30% after 2 years from a crisis. Therefore, we hypothesize that countries heavily depending on credit suffer larger banking crisis effects, and the hypothesis is supported by our data.

The second objective is to identify factors that are associated with the excess loss of non-life insurance consumption. First, we investigate subcategories of non-life insurance: motor insurance, property insurance and liability insurance. Second, we sort and partition countries by country's income level. Third, we evaluate the marginal contribution of the price of insurance. Fourth, we test whether the post-crisis behavior of credit and investment would explain the loss of non-life insurance consumption. Broadly speaking, non-life insurance is used by households and firms to protect investments, and the decline in non-life insurance premiums relative to GDP may suggest a shift away from higher-risk and higher-return investments toward safer activities, a shift that is mirrored in the banking system's shift away from private credit toward safer investments after a financial crisis (Demirguc-Kunt et al., 2006). For this reason, we test whether a decline in credit and investment is associated with the persistent loss of non-life insurance premiums. However, our tests do not support the explanation of risk shifting hypothesis. We further investigate the exposure effect on motor insurance consumption.

This study also contributes to the literature on insurance consumption. Several studies have analyzed the determinants of insurance demand (e.g., Truett and Truett, 1990; Browne and Kim, 1993; Outreville, 1996; Browne et al., 2000; Ward and Zurbruegg, 2002), while others have studied the nexus between insurance and economic growth (e.g., Ward and Zurbruegg, 2000; Zeits, 2003; Hussels et al., 2005; Outreville, 2012) or the determinants of insurance market growth (see, for instance, Enz, 2000; Zheng et al., 2008; Zheng et al., 2009) by modeling the relationship between GDP and measures of insurance consumption. However, to our knowledge, this is the first study to evaluate the impact of banking crises on non-life insurance markets quantitatively and to investigate the factors that are associated with post-crisis effects.

The remainder of this paper is organized as follows. In Section 2, we discuss our methodology and data, and evaluate the marginal impact of banking crises on non-life insurance consumption by country credit groups. The robustness of our findings is also discussed. Furthermore, we attempt to explain the post-crisis effect by decompose the factors of our basic model. In Section 3, we test the risk shifting hypothesis. Further, we consider the effect of exposure in Section 4. A summary of our findings and a discussion of the limitations of our work are given in Section 5.

2. Identifying the Impact of Banking Crises on Insurance Consumption

2.1. Methodology

To evaluate the impact of banking crises on non-life insurance consumption, we first construct indicators of banking crises and estimate the shock of a banking crisis observed on the parameter values.

We compare the relationship between the level of country's bank credit and the effects of banking crisis by sorting and partitioning countries based on the level of country's credit by banking sector. Following Rioja et. al. (2102), we sort countries by *bank private credit*, which represents the financial resources provided to the private sector by domestic money banks as a share of GDP (see Table 2-4 for the definition and the summary statistics).

Using an average value of the credit measure over the sample period, we categorize countries into three groups with high, middle and low credit with similar number of sample countries. Note that the country classification by using the average over the sample period eliminates the effect of temporary fluctuations in credit activity. Thus, this sorting is not subject to the crisis effect on credit.

To construct a simple test of whether the occurrence of a banking crisis is followed by a significant change in non-life insurance consumption, we estimate the following linear model. In our basic model, insurance penetration (premium as a percent of GDP) denoted by y_{it} is determined by

$$y_{it} = \alpha_i + \alpha_t + \sum_{s=0}^{9} \delta_s Crisis_{i,t-s} + \boldsymbol{\theta} \mathrm{X}_{it} + \varepsilon_{it} \tag{1}$$

where $Crisis_{it}$ is indicator variable that takes on a value 1if there is a banking crisis in country i at year t, α_i represents a country fixed-effect for country i, α_t represents a year fixed-effect for year t, and ε_{it} is a normally distributed error term. The control variables denoted by X_{it} include the one-year lagged GDP per capita as a proxy for income level in the basic model. Later, we introduce other variables to capture associated factors.

Joint F-tests indicate that country fixed effects are present at 1% significance for all models. The number of lags for crisis variable is restricted to 9 (10-year window from the year of crisis occurrence). The joint F-tests for the crisis variables and year dummies are reported with parameter estimates. We estimate the model on the panel data from 139 countries over the period 1988 through 2010.

Our primary interest lies in the coefficients of crisis terms, δ, which capture the shock of the banking crises on insurance consumption in a post-crisis period. We use insurance penetration as a measure of insurance consumption because 1) the measure changes only when insurance premium volume and GDP move with a different proportion and 2) the measure is isolated from inflation rate and currency exchange rate. The crisis parameters take a negative value in a post-crisis period only when 1) the proportional decline of non-life insurance premium is larger than that of GDP and 2) the proportional recovery of non-life insurance premium is smaller than that of GDP. If the difference of the shock on non-life insurance consumption and GDP is simply a matter of timing, we expect to observe both positive and negative signs in a post-crisis period. For instance, the order of the signs would be positive signs followed by negative signs if output drops and recover faster than non-life insurance consumption does. Thus, a consistent negative coefficient for crisis variables implies excess negative proportional loss of non-life insurance consumption in a post-crisis period.

In the basic model, we use one control variable: one-year lagged GDP per capita because the positive relationship between per capita output as a proxy for income and insurance consumption is a robust finding in the literature (see Outreville, 2012). Although penetration is controlled by GDP by its definition, penetration may comove with output level especially in middle income countries (e.g., Enz, 2000). We use the log-transformed per capita GDP as an output measure.

2.2. Data

Our source of banking crisis events is the banking crisis episodes listed by Reinhart and Rogoff (2008, 2011). They define two types of events: "(1) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions; and (2) if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions) that marks the start of a string of similar outcomes for other financial institutions." Using this definition, Reinhart and Rogoff (2008) identify 196 banking crises from 1968 to 2007.[5] The banking crisis events are updated by Reinhart and Rogoff (2011) who include banking crisis event up to 2010 (See Appendix I for the banking crisis events used in our analyses).[6]

The frequency of banking crises has varied over time (see Figure 5). For instance, only two banking crises occurred from 1966 to 1975, whereas 32% and 49% of all crises occurred in the 1980s and the

[5] Our sample up to 2007 represents the sum of the banking crisis events listed in Table A5 and Table A3 of Reinhart and Rogoff (2008).
[6] Reinhart and Rogoff (2011) focus on 70 countries which do not fully cover our sample. For a robustness check, we estimate the marginal post-crisis effects without updating the crisis data by Reinhart and Rogoff (2011). Our findings are consistent between the samples. See Section 2.4 B.

1990s, respectively. Following a peak in frequency during the period 1991-95, with 73 crises, this trend declines in the latter years of the sample, and only five crises occurred in the period 2001-05. The increase in the period 2006-2010 reflects the 2007-2008 global financial crisis (18 banking crisis events) after the bursting of the U.S. housing bubble.

Using the data on banking crisis events, we construct a dummy variable denoted by *Crisis* that takes the value 1 for the year when a banking crisis started for the sample period of 1988-2010, and 0 otherwise. The crisis variable is expanded by a lagged crisis variable, *Crisis Lt* (where *t*=1,..,9) that takes the value 1 when a banking crisis started *t* years before, and 0 otherwise. This specification allows us to estimate the during-crisis and post-crisis effect up to 10 years after the onset of a crisis.

The crisis variables are summarized on the left side of Table 1 by country bank private credit group. The *Crisis* variable count and the likelihood of a banking crisis is the highest in the middle credit countries (47 crises and 4.8%) and the lowest in the low credit countries (27 crises and 3.1%). Note that the counts of the lagged crisis variables can be larger than *Crisis* because *Crisis* includes crises that occurred from 1988 to 2010, whereas the lagged variables include crises that occurred before 1988. For instance, the 1984 US banking crisis triggered by the failure of Continental Illinois is not counted in *Crisis* in the high credit countries because it occurred before our sample period, but is included in the lagged variables in the US (from *Crisis L*4 in 1988 to *Crisis L*9 in 2003).

Country-level insurance data, gross written premiums and loss ratios, are taken from Axco Global Statistics.[7] The premium data cover 139 countries in our sample period from 1988 to 2010.[8] We apply Winsorisation at 1% to reduce the effect of spurious outliers for penetration variables. The summary statistics of the variables are provided in Tables 2 and 4 by country credit group.

The data on country-year banking crises and insurance premiums are matched with other variables such as GDP per capita retrieved from the World Development Indicators of the World Bank. The matched data contain 2,354 country-year observations. The number of observations used in our analyses is further reduced because many countries do not report premium and loss ratios by subtype of non-life insurance.

2.3. Results

[7] The loss ratio is calculated in two ways depending on data availability: one is paid loss divided by written premiums and the other is incurred loss divided by earned premium.
[8] Data for 2011 are available for many countries in the Axco Global Statistics as of April 2012, but are not used in our analysis because banking crisis events and many variables from the World Bank are not available.

We conduct several tests to validate the model. First, we investigate potential heteroskedasticity by checking the relationship between the standardized residuals and predicted values. The White tests do not reject homoskedasticity for all credit groups. To reduce the concern further, we report cluster robust standard errors. Second, normality tests support the normality assumption. Third, we consider both random-effects model and fixed-effects model first, and run Hausman tests. The tests reject random-effects model as a preferred mode. We also consider the pooled cross-section model. Yet, F-tests indicate the significance of country fixed-effects and reject the model. Therefore, the following discussion focuses on the results obtained from the OLS-based fixed-effects models.

A. Effect of Banking Crises on Non-life Insurance Consumption

Table 5 shows the parameter estimates for the models of non-life insurance total by country groups based on bank private credit.[9] An intercept, year dummy variables, and country dummy variables are included in all models, but the parameter estimates are omitted. F-tests for crisis dummies and those for year dummies are reported after the parameter estimates.

For high-credit countries, a negative and significant effect stretches over 3 years, and all lagged crisis variables shows negative signs. The largest negative effect of a crisis can be found in the 4th year from a crisis year (3-year lag). The coefficient indicates that the non-life penetration decreases by 0.144 percentage points, meaning that the mean non-life total premium decreases by 7.5% (= -0.144/1.9). We define the cumulative effect of the shock as the sum of the parameter estimates for all crisis variables, $\sum_{s=0}^{9} \delta_s$. The cumulative effect indicates that about 38% (=-0.73/1.9) of the annual premium is lost in the 10-year post-crisis window. Note that the identified premium loss is excess loss which cannot be explained by output. That is, the negative signs imply that the recovery of non-life insurance consumption from a banking crisis takes longer that output recovery.

The contrast between high credit countries and other groups is clear from the table. The significant and negative effects are concentrated only in the high credit countries. Thus, economies heavily depending on bank credit tend to suffer loss of non-life insurance premium. Our findings provide another evidence of prolonged adverse effect of banking crises.

The findings are consistent with the literature with several respects. First, the literature shows that countries with low financial development tend to have relatively small impact of credit disruptions on economy (e.g., Bencivenga and Smith, 1991). Our estimation results show that non-life insurance consumption is unaffected by banking crises in the middle and low credit groups.

[9] Bank private credit: Low ≤ 18%, 18% < Middle ≤ 44%, and High < 44%. Countries included in each credit group and its mean bank private credit is reported in Appendix II

Second, the identified negative shock in the high credit countries may be an evidence of the consequence of cutbacks of bank lending during post-crisis periods, which may hinder real activity (Dell'Ariccia et al., 2008). In addition, considering a larger fraction of bank private credit is allocated to households with less choice of alternative financing (Beck, Buyukkarabacak, Rioja, and Valev, 2012), we believe that the contrast between credit groups show that the impact of a crisis depends on the availability of alternative financing (Levine and Zervos, 1998, De Gregorio and Guidotti, 1995).

B. Sorting Countries by Alternative Credit Measures

To evaluate the effect of other financial institutions providing credits and the effect of bank credit to public sectors, we prepare two additional credit measures to sort countries: *private credit* and *bank credit*. The former is defined by domestic private credit provided by deposit money banks and other financial institutions to GDP and the latter is defined by domestic credit provided by deposit money banks and other financial institutions to all sectors. Thus, the bank credit measure is the most comprehensive and includes credit provided by non-deposit money banks and to public sectors. The private credit measure is broader than bank private credit measure because the private credit measure covers private credit provided by other financial institutions.

Tables 6 and Table 7 show the parameter estimates for countries sorted by private credit and bank credit. As observed, we do not identify significant difference in parameter estimates between the tables. This implies that additional sources of credit (e.g. non-bank and securitization) and the role of bank credit to public sector do not substantially affect the magnitude of crisis effects.

C. Detrending Bank Private Credit Measure

Our credit measures used for sorting countries are simply the average value over the sample period. One potential issue of the simple average is the upward trend of credit measures. As shown in Figure 6, all three credit measures have increased by 20 percentage points in the last 15 years. Taking the average of a credit measure, we overvalue observations in the recent years and economies observed only in recent years tend to have a higher average value.

To avoid such a bias, we take the average after removing year effects. This is done by running an OLS regression of credit measures only on year dummies and taking the average value of the residuals. We sort countries by the alternative credit measures and run Eq. 1. Table 8 reports the estimation results for bank private credit. The difference from Table 5 is that the negative coefficients in the high credit countries and the positive coefficient observed in the middle credit countries become more significant. Yet, we find that the overall result is consistent with Table 5. Although results are not reported, similar consistency is observed when countries are sorted by other two credit measures.

D. Insurance Density Measure

To make sure that our findings do not depend on the choice of insurance consumption measure, we replace the dependent variables with the logarithm of insurance density defined by the per capita value of non-life insurance premiums. Although the dependent variable is not controlled by GDP, we have GDP per capita in the right hand side of Eq.1. Therefore, crisis variables are expected to capture insurance consumption which cannot be explained by output level.

The results for the non-life density measure are reported in Table 9, in which the parameter estimates for the high credit countries show significant and negative signs in a post-crisis period. The negative crisis effects are concentrated in the high credit countries. The estimated parameter values are not directly comparable with those in other tables, but we can interpret that the magnitude of the cumulative negative effect is 44%, which is slightly larger than that observed in Table 5. In addition, we observe positive effects in the middle credit countries again. A major difference from penetration models is that output variable is positive and significant in all groups as expected. Thus, we confirm that our findings are consistent between insurance consumption measures.

E. Alternative Penetration Measure

While our non-life insurance penetration excludes health insurance premium because our purpose is to evaluate the effect of banking crises on insurance consumption through the shock on bank lending, non-life penetration measure tends to include health insurance premium in practice. For instance, insurance penetrations annually reported by Swiss Re Sigma, arguably one of the most frequently used in the related literature includes health insurance premium in the non-life total premium. The difference between the two non-life penetration measures is not significant for most countries where public health care system plays an important role of country's health care, while it is not innocuous for those countries heavily depending on private health insurance such as the United States and Netherland because of the large proportion of the premium.

To investigate the effect of including health insurance, we repeat parameter estimations by using the non-life penetration constructed by Swiss Re.[10] The results reported in Table 10 are consistent with the results in Table 5 in that negative and significant crisis effects are observed in high credit countries. The magnitude of the crisis effects and the significance are slightly larger when the alternative penetration measure is used. Thus, our finding of crisis effects is robust to an alternative penetration measure.[11]

F. Exogeneity of Banking Crisis

[10] Data is available from Swiss Re Sigma, various years.

[11] On an additional note, we find no banking crisis effect on life insurance consumption.

Although our purpose is not to establish the causality between banking crises and insurance consumption, we are interested in the potential endogeneity of banking crises to interpret the OLS-based estimates presented above. Therefore, the presence of engogeneity is formally tested. This is done by estimating a Probit model which expresses the probability of a crisis occurrence as a function of past insurance consumption measure and other variables (Furceri and Mourougane, 2012):

$$Prob(Crisis_{it} = 1) = F\left(\alpha + \sum_{s=1}^{9} \delta_s Crisis_{i,t-s} + \boldsymbol{\theta}\mathrm{X}_{it-1} + \varepsilon_{it}\right)$$

Table 11 summarizes the estimation results for each type of insurance in the high credit countries, and suggests that none of the explanatory variables explain the occurrence of banking crises. The assumption of exogeneity of the banking crisis variable to insurance penetration is proved to be valid.

2.4. Decomposition of the Crisis Effect

We argue that the identified negative shock on non-life insurance consumption in the high credit countries is an evidence of cutbacks of bank lending during post-crisis periods. A natural follow-up question is why non-life insurance consumption adversely deviates from the national output during a post-crisis period in the higher-credit countries. The estimation results documented above does not provide an explanation about the excess loss. This is an important question because investigating the factors associated with the premium loss may provide insights on banking crisis effect, which contrasts with the quick recovery of aggregate output.

A. Effect of Banking Crises on Types of Non-life Insurance

Since non-life penetration is the total of a variety of types of insurance, we are interested in identify the crisis effect on each type of insurance and the source of the premium loss in the high credit countries. We break down non-life total into the primary subcategories of motor insurance, property insurance, and liability insurance and repeat parameter estimations for each subcategories.[12]

Table 12 summarizes the parameter estimates of motor insurance by credit groups. Persistent and negative signs are observed in the high credit countries. The negative effect on motor insurance starts without a lag and remains significant for 10 years. The deepest decline is observed in the 4th year since a crisis. The coefficient indicates that motor penetration drops by 0.149 percentage point and that the estimated magnitude is slightly greater than the largest decline in non-life insurance by 0.144 in Table 5. Thus, we confirm that the primary contributor of the non-life penetration loss is motor

[12] We test for the exogeneity of contemporary crisis variable for each subcategory, and found that no variables explain the occurrence of a banking crisis.

insurance. The magnitude of the penetration loss can be interpreted as 17% (=0.149/0.89) loss of the annual premium in the year. After the 4th year, the magnitude of the negative effect monotonically diminishes over the post-crisis period. The cumulative effect of the shock on motor insurance reaches to 101 percentage points which is 113% (=-1.01/0.89) of the annual premium over a 10-year post-crisis window. Again, patterns observed in other credit groups are quite different from those observed in the high credit countries. Overall, the results are consistent with non-life total as expected because of a large fraction of motor insurance in non-life insurance market.

Table 13 reports the estimation results for property insurance. Crisis effects are found to be insignificant in a 10-year window for all income groups with one exception in the low credit countries, while the joint F-tests indicates that the 10-year post-crisis window is significant for the high credit countries. None of the coefficients for lagged income are significant. Table 14 summarizes the estimation results for liability insurance. The results are mixed in that the positive crisis effect is present in the middle credit group, whereas no crisis effect is confirmed for the high credit group. The time lag between the occurrence of a crisis and the positive effect observed in the middle crisis countries may be explained by the recovery of liability insurance consumption is faster than that of output.

B. Effect of Banking Crises by Country Income Group

Given that the volume of insurance consumption is heterogeneous in income level (e.g., Enz, 2000) and in type of insurance (e.g., Browne et al., 2000), we partition the country samples to examine any differential impact of a shock on countries according to both their income level (high, upper-middle, lower-middle and low) and type of insurance (non-life total, motor, property and liability).[13]

Tables 15 show the parameter estimates for the models of non-life insurance total by country income groups. For the high-income countries, a negative and significant effect stretches over 4 years, and all lagged crisis variables shows negative signs. The largest negative effect of a crisis can be found in the 4th year from a crisis year (3-year lag). The coefficient indicates that the non-life penetration decreases by 0.249 percentage points and the cumulative effect reaches 1.18 percentage points. Interestingly, both figures are 60-70% larger than those observed by bank private credit classification in Table 5.

The contrast between higher income countries and lower income countries is clear. The significant and negative effects are concentrated in the high income countries, and the lower-middle income countries tend to exhibit positive effects. Our findings support the hypothesis that economic activities do not recover to the level of the pre-crisis period quickly in advanced economies (see, for instance,

[13] Country classification is based on the World Bank income categorization.

Reinhart and Rogoff, 2008). Lagged output variable shows the positive and significant effect in the upper-middle and low income countries. This means that the level of non-life insurance penetration tends to increase as output level increase in the income groups.

Table 16 summarizes the parameter estimates of motor insurance by income groups. Persistent negative signs are observed in the high income countries. The negative effect on motor insurance starts without a lag and is concentrated in the first eight years. The deepest decline is observed in the 4th year since a crisis. The coefficient indicates that motor penetration drops by 0.198 percentage point and the cumulative effect reaches 1.19, which is slightly larger than that for non-life total. This also shows that motor insurance is the primary factor of non-life premium loss in a post-crisis period.

C. Effect of Supply Shock

One of challenges of identifying the effect on insurance consumption is that the measure is based on aggregate premium volume. Since premium is a product of premium rate and indemnity amount, estimated effect on premium volume can be explained by both change in premium rate and change in indemnity amount. One potential explanation of the reported negative effect on insurance penetration is that premium volume dropped simply because increased premium rate after a crisis reduced demand for coverage.

To separate the crisis effects from the price effect, we control for the price of insurance. Insurance price measure, defined by the 1-year lagged log-transformed inverse of loss ratio (Esho et al., 2004), is expected to capture several factors.[14] Insurance regulators may impose trade barriers to protect their local insurance industry, and the exclusion of foreign insurers in a country may reduce competition and thus raise prices. This protection policy could therefore result in lower insurance consumption. Countries may also differ in terms of financial infrastructure, which could lead to large differences in insurance production costs. Regardless of the reason, it is expected that insurance prices will be negatively related to non-life insurance consumption. For instance, Browne, Chung, and Frees (2000) use foreign firm market shares as a proxy for the price of insurance and find a negative relationship with motor insurance but a positive relationship with liability insurance.

Controlling for price effect is particularly important to evaluate the effect of financial crises because large adverse shocks to the financial condition of insurers can substantially reduce industry capacity. Therefore, post-crisis premium volume decrease in the high credit countries may be explained by supply shock described as underwriting cycle in non-life insurance markets (e.g., Gron, 1994).

[14] Winsorisation is applied to reduce the effect of spurious outliers observed for insurance price measures which can be severely fluctuated by large and small loss ratios. The price variables are treated at 10% (95 percentile and 5 percentile).

According to the capacity-constraint hypothesis, when capacity is reduced by a financial crisis, the short-run supply curve shifts to the left, resulting in higher price and lower quantity. Figure 7 illustrates that the aggregate premium volume (Q times P) decreases if price elasticity of demand is sufficiently high.

Using one-year lagged logarithm of inverse loss ratio as a proxy of insurance price, price is found to be insignificant in all credit groups (see Table 17). That is, the price level is not associated with the proportional level in non-life insurance consumption. Furthermore, the price variable marginally contributes increasing the magnitude of crisis effect. Similar results are observed in motor insurance penetration. Therefore, we conclude that reduced insurance consumption after a crisis is not attributed to demand decline through price change after banking crises.

In summary, we find that premium volume decline after a banking crisis tends to be associated with the high income countries and that most of the premium decline in non-life insurance total can be explained by premium decline in motor insurance. In addition, the premium loss cannot be explained by supply shock.

3. Risk Shifting in the Post-Crisis Period

A line of potential explanation of the excess decline in non-life insurance consumption is risk shifting in bank's lending. In particular, we are interested in investigating a set of factors of banking credit and investment. Empirical studies show that banking crises are accompanied by a decline in credit to the private sector and aggregate economic output (see Kaminsky and Reinhart, 1999; Eichengreen and Rose, 1998; Demirgüç-Kunt et al., 2006). It is also well documented that credit cycles often coincide with cycles in economic activity. For instance, using micro data, Mendoza and Terrones (2008) show a strong relationship between credit to the private sector and measures of firm values, external financing, and leverage. One scenario is that an adverse shock causes a decline in aggregate demand, leading firms to reduce or delay risky investment and working capital and demand for bank credit. Another scenario is that the shock impairs the balance sheets of the borrowers and increases asymmetric information, leading banks to reduce their lending to borrowers.

The literature on investment argues that the impact of risk on investment could be large because investment expenditure tends to be an irreversibly sunk cost and because firms usually have options over the timing of their investments (see, for instance, Pindyck, 1991; Pindyck and Solimano, 1993). Therefore, investment expenditure becomes very sensitive to uncertainty regarding future payoffs. Rioja, et al. (2012) document that households and firms actually reduce risky investments after a banking crisis, and the level of investment does not recover for many years despite recovery of aggregate output.

To investigate the relationship of a post-crisis behavior between credit/investment and non-life insurance consumption, we consider: bank private credit and investment representing the formation of national gross capital. Table 18 shows the estimated parameters for the models with the credit/investment variables and indicates that none of the credit/investment variables are statistically significant. Although the results are not reported, we also repeat parameter estimations for motor insurance penetration and confirm no significant effect of credit and investment variables. Thus, we find no evidence that a decline in bank credit to the private sector (see Figure 4) and a decline in investment (Rioja, et al., 2012) in a post-crisis period are associated with the excess decline of non-life insurance consumption. This result does not support the potential explanation that risk-shifting of banks' lending after a crisis is a factor of excess loss of non-life insurance consumption.

4. Effect of Exposure to Potential Loss

Identifying factors associated with the decline of motor insurance consumption is important also because the exposure to risk of buying and using a motor vehicle may represent a major portion of household risk. A change in motor insurance consumption in a post-crisis period may provide implications about the risk-taking behavior of households and firms.

After controlling for the price level and output level, several motor insurance specific factors may be able to explain the post-crisis excess loss on motor insurance consumption, although not exclusively. First, the number of motor vehicles on the roads may drop excessively after a crisis because households and firms substitute public transport for private vehicles. Second, the value of motor vehicles on the roads drops and does not return to the pre-crisis level because motor vehicles are not replaced by new vehicles as frequently as before a crisis. Third, the demand for motor insurance is simply reduced after crises because it is insensitive to the recovery of output level or/and because the degree of risk aversion decline. There are significant differences between the first two explanations and the third, in that the former implies that the post-crisis effect follows a decline in risk exposure, whereas the third implies greater risk-taking after crises.

Here we prepare variables to test whether the post-crisis effect can be explained by the level of risk exposure. The first variable is road energy consumption, which measures the extent of use of motor vehicles (see Tables 2 and 4 for the definitions and summary statistics of the variables). The use of motor vehicles and the number of vehicles on the road are accompanied by the energy consumption.

Therefore, an excessive decrease in motor vehicle use after a crisis is expected to be captured by the change in road energy consumption. The second variable is household expenditure on motor vehicle purchases as denoted by household vehicle, which is used as a proxy for the value of motor vehicles, that is, the value of insurable assets for 1st party and 3rd party coverage. If the value of motor vehicles decreases excessively after a crisis and then adversely affects motor insurance consumption, then this variable is expected to capture the effect.

According the data, both measures decrease after crises. In the high-credit countries, the decline in the road energy consumption lasts for a long time, whereas household expenditure on motor vehicle purchases shows a sharp drop in the aftermath and a v-shaped recovery over the next five years.

Table 19 summarizes the estimation results for motor insurance in the high income countries. Note that the sample size of the models (2) and (3) substantially reduced because the household vehicle expenditure variable covers only OECD countries. The results indicate that neither of them is significant. Yet, the estimated magnitude of the crisis effect tends to be substantially intensified in model (2) and (3). As a consequence, the cumulative crisis effect is actually increased by 85% from our basic model.

Note that the household vehicle expenditure is closely related to the output level and the parameter for the output is intensified by including the household vehicle expenditure variable. Therefore, the theoretical motor insurance consumption tends to be increased due to output decline in a post-crisis period. Thus, instead of explaining the excess loss of motor insurance consumption, the level of risk exposure actually predicts greater crisis effect in motor insurance consumption.

One interpretation for the predicted greater crisis effect is that households and firms in the high-credit countries reduce motor insurance coverage after crises due to their tight budgets, possibly by increasing deductibles or by reducing policy limits, and do not raise it back to the pre-crisis level even after the recovery of their income.

5. Conclusion

Insurance consumption can primarily be explained by the level of income on an individual level or national output in aggregate. Therefore, banking crises that adversely affect individual income and national output also reduce insurance consumption. From past experience of a long-term reduction in non-life insurance consumption after banking crises, we hypothesize that there are additional impacts that cannot be explained by the level of income or aggregate output, and investigate the marginal effect of banking crises on non-life insurance consumption.

Using well-known banking crisis episodes collected by Reinhart and Rogoff (2008, 2011), we show that the countries heavily depending on bank credit experience an excess decline in non-life insurance consumption after banking crises. This post-crisis effect is long lasting, and the magnitude of the premium loss is significant in the high-credit countries. Our evidence shows that the post-crisis effect on non-life insurance consumption contrasts sharply with the rapid recovery of aggregate output and the banking sector. We find the primary contributing factor of the premium loss is motor insurance which suffers a sharp decline in consumption immediately after a crisis and have persistent negative effect which adds up to 113% of the mean premium in a 10-year post-crisis window in the high credit countries. Furthermore, classifying countries by income level, we find that the magnitude of non-life premium loss is increased by 60-70% in the high-income countries.

To understand the long-lasting effect of banking crises, we investigate price effect, risk-shifting effect and exposure effect, and find that none of those factors explain the excess loss of premium. We find that the post-crisis behavior of risk exposure increases the magnitude of excess loss of motor insurance consumption by 85% in the high-credit countries. Thus, the value and the use of motor vehicle predict more motor insurance consumption than consumed after crises. One potential explanation is an increase of households' and firms' risk-taking after a banking crisis probably due to lack of risky investment opportunities. We leave testing the hypothesis for future research.

Several immediate extensions of this study require further examination. Among these, the post-crisis effect in the high-income countries could be investigated more extensively by focusing only on OECD countries, for which more detailed data are available. Second, how financially affected insurers reduce their supply of non-life insurance coverage in the post-crisis period merits investigation.

Appendix 1: Banking Crisis Events - Source: Reinhart and Rogoff (2008, 2011)

Country	Banking Crisis Year	Country	Banking Crisis Year
Albania	1992	Kenya	1985 1992 1996
Algeria	1990	Korea	1985 1997
Angola	1991	Kuwait	1983
Argentina	1980 1985 1989 1995 2001	Kyrgyz Republic	1993
Armenia	1994	Lao People's Dem Rep.	1992
Australia	1989	Latvia	1994
Austria	2008	Lebanon	1988
Azerbaijan	1995	Lesotho	1988
Bangladesh	1987	Liberia	1991
Belarus	1995	Lithuania	1995
Belgium	2008	Macedonia	1992
Benin	1988	Madagascar	1988
Bolivia	1987 1994 1999	Malaysia	1985 1997
Bosnia & Herzegovina	1992	Mali	1987
Botswana	1994	Mauritania	1984
Brazil	1985 1990 1994	Mauritius	1997
Brunei	1986	Mexico	1981 1994
Bulgaria	1994	Morocco	1983
Burkina Faso	1988	Mozambique	1987
Burundi	1994	Myanmar	1996
Cameroon	1987 1995	Nepal	1988
Canada	1983	Netherlands	2008
Cape Verde	1993	New Zealand	1987
Central African Rep.	1976 1988	Nicaragua	1987 2000
Chad	1976 1981 1983 1992	Niger	1983
Chile	1976 1980	Nigeria	1992 1995
China	1992 1992	Norway	1987
Colombia	1982 1998	Panama	1988
Congo, Democratic Rep.	1982 1991 1994	Papua New Guinea	1989
Congo, Republic of	1992	Paraguay	1995 1998 2002
Costa Rica	1987 1994	Peru	1983 1999
Cote D'Ivoire	1988	Philippines	1981 1997
Croatia	1996	Poland	1991
Czech Republic	1994 1991	Portugal	2008
Denmark	1987 1992 2008	Romania	1990
Djibouti	1991	Russia	1995 1998 2008
Dominican Republic	1996 2003	Rwanda	1991
Ecuador	1980 1994 1996 1998	Sao Tome and Principe	1991
Egypt	1981 1990	Senegal	1988
El Salvador	1989 1998	Sierra Leone	1990
Equatorial Guinea	1983	Singapore	1982
Eritrea	1993	Slovakia	1991
Estonia	1992 1994 1998	Slovenia	1992
Ethiopia	1994	South Africa	1977 1989
Finland	1991	Spain	1977 2008
France	1994 2008	Sri Lanka	1989
Gabon	1995	Swaziland	1995
Gambia	1985	Sweden	1991 2008
Georgia	1991	Switzerland	2008
Germany	1977 2007	Tajikistan	1996
Ghana	1982 1997	Tanzania	1987
Greece	1991 2008	Thailand	1979 1983 1996
Guatemala	1991 2001 2006	Togo	1993
Guinea	1985 1993	Trinidad & Tobago	1982
Guinea-Bissau	1995	Tunisia	1991
Honduras	1999 2001	Turkey	1982 1991 1994 2000
Hong Kong	1982 1998	Uganda	1994
Hungary	1991 2008	Ukraine	1997
Iceland	1985 1993 2007	United Kingdom	1974 1984 1991 1995 2007
India	1993	United States	1984 2007
Indonesia	1992 1994 1997	Uruguay	1971 1981 2002
Ireland	2007	Venezuela	1978 1993
Israel	1977 1983	Vietnam	1997
Italy	1990 2008	Yemen	1996
Jamaica	1994	Zambia	1995
Japan	1992	Zimbabwe	1995
Jordan	1989		

Appendix II: Country Classification by the Mean Bank Private Credit

High Credit		Middle Credit		Low Credit	
country	Mean	country	Mean	country	Mean
Australia	80.2	Bangladesh	27.3	Afghanistan	7.2
Austria	99.5	Bolivia	39.8	Angola	5.8
Belgium	69.1	Brazil	33.6	Albania	12.6
Bosnia and Herzegovina	47.3	Cote d'Ivoire	20.8	Argentina	15.5
Canada	92.3	Colombia	26.6	Armenia	8.7
Switzerland	154.9	Costa Rica	23.2	Azerbaijan	6.7
Chile	63.8	Dominica	21.5	Burundi	13.7
China	94.3	Ecuador	22.5	Benin	12.6
Cyprus	146.8	Egypt	37.5	Burkina Faso	12.9
Czech	48.7	Guatemala	19.1	Belarus	13.0
Germany	107.8	Honduras	33.9	Botswana	14.7
Denmark	88.7	Croatia	43.1	Central Africa	5.7
Spain	108.0	Hungary	36.7	Cameroon	12.3
Estonia	48.0	Indonesia	32.2	Algeria	17.0
Finland	70.9	India	29.2	Ethiopia	12.2
France	91.1	Jamaica	21.7	Gabon	9.6
UK	134.1	Kazakhstan	22.3	Georgia	12.9
Greece	51.6	Kenya	23.0	Ghana	8.5
Hong Kong	144.7	Kosovo	20.1	Guinea	4.0
Ireland	103.4	Sri Lanka	23.0	Gambia	11.4
Israel	71.8	Lithuania	22.9	Haiti	12.6
Italy	71.7	Latvia	33.8	Kyrgyz	6.0
Jordan	67.9	Mexico	18.3	Cambodia	9.8
Japan	146.4	Macedonia	26.4	Lao PDR	7.2
Korea	68.3	Mauritania	26.1	Lesotho	13.2
Lebanon	66.7	Nicaragua	27.9	Moldova	17.3
Morocco	44.2	Nepal	24.0	Mali	13.9
Mauritius	52.7	Pakistan	23.5	Mongolia	17.1
Malaysia	107.4	Philippines	28.2	Mozambique	12.1
Namibia	46.7	Papua New Guinea	18.8	Malawi	6.8
Netherlands	125.0	Poland	24.1	Niger	8.3
Norway	63.7	Paraguay	22.1	Nigeria	14.1
Panama	68.4	Russia	19.7	Peru	16.2
Portugal	102.9	Saudi Arabia	26.9	Romania	17.6
Singapore	90.9	Senegal	20.9	Rwanda	8.0
Sweden	64.8	Serbia	28.6	Sierra Leone	6.3
Thailand	103.3	Slovakia	41.7	Swaziland	16.2
Tunisia	53.4	Slovenia	43.0	Syria	9.7
United States	52.4	Togo	18.5	Tajikistan	13.2
Vietnam	51.1	Trinidad and Tobago	29.5	Turkey	17.8
South Africa	62.2	Ukraine	22.1	Tanzania	6.5
		Venezuela	19.6	Uganda	5.6

References

Beck, T., B. Buyukkarabacak, F. Rioja, and N. Valev, 2012, Who Gets the Credit? And Does It Matter? Household vs. Firm Lending Across Countries, B.E. Journal of Macroeconomics, 12(1) (Contributions), Article 2.

Bencivenga, V. and B. Smith, 1991, Financial Intermediation and Endogenous Growth, Review of Economic Studies, 58(2), 195 – 209.

Browne, M., J. Chung, and E. W. Frees, 2000, International Property-Liability Insurance Consumption, Journal of Risk and Insurance, 67(1), 73-90.

Browne, M. J. and K. Kim, An International Analysis of Life Insurance Demand, Journal of Risk and Insurance, 60(4), 616-634.

Caprio, Gerard, and Daniela Klingebiel, 1996, "Bank Insolvencies: Cross-Country Experience." Policy Research Working Paper No.1620, World Bank.

Caprio, Gerard, Daniela Klingebiel, Luc Laeven, and Guillermo Noguera, 2005, "Appendix: Banking Crisis Database," in Patrick Honohan and Luc Laeven (eds.), Systemic Financial Crises: Containment and Resolution. Cambridge, U.K.: Cambridge University Press.

Cerra and Saxena, 2008, Growth Dynamics: The Myth of Economic Recovery, American Economic Review 2008, 98(1), 439–457.

De Gregorio, J., and P. Guidotti, 1995, Financial development and economic growth, World Development 23(3), 433 – 448.

Dell'Ariccia, G., E. Detragiache, and R. Rajan, 2008, The Real Effect of Banking Crises," Journal of Financial Intermediation 17 (1):89-112.

Demirgüç-Kunt, A., E. Detragiache and P. Gupta, 2006, Inside the crisis: An empirical analysis of banking systems in distress, Journal of International Money and Finance, 25(5), 702-718.

Dionne, G. and L. Eeckhoudt, 1984, Insurance and Saving: Some Further Results, Insurance: Mathematics and Economics 3(2),101-110.

Eichengreen, B., and A. Rose, 1998, Staying Afloat When the Wind Shifts: External Factors and Emerging-Market Banking Crises, NBER Working Series 6370.

Enz, R., 2000, The S-Curve Relation Between Per-Capita Income and Insurance Penetration, Geneva Papers on Risk and Insurance, 25(3), 396-406.

Esho, N., A. Kirievsky, D. Ward, and R. Zurbruegg, 2004, Law and the Determinants of Property-Casualty Insurance, Journal of Risk and Insurance, 71(2), 265-283

Furceri, D. and A. Mourougane, The effect of Financial Crises on Potential Output: New Empirical Evidence from OECD countries, Journal of Macroeconomics, 34(3), 822-832.

Furceri, D. and A. Zdzienicka, 2011, The real effect of financial crises in the European transition economies. Economics of Transition, 19: 1–25.

Gron, A., 1994, Capacity Constraints and Cycles in Property-Casualty Insurance Markets, RAND Journal of Economics 25(1), 110-127.

Kaminsky, G., and C. Reinhart. 1999, The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. American Economic Review, 89(3): 473–500.

Laeven, Luc, and Fabian Valencia, 2008, Systemic Banking Crises: A New Database, IMF Working Paper WP/08/224.

Levine, R. and S. Zervos, 1998, Stock Markets, Banks, and Economic Growth, American Economic Review 88(3), 537 – 558.

Mayers, D. and C. Smith, 1983, The Interdependence of Individual Portfolio Decisions and the Demand for Insurance, Journal of Political Economy, 91(2), 304-311.

Mendoza, E. and M. Terrones, 2008, An Anatomy Of Credit Booms: Evidence From Macro Aggregates And Micro Data, NBER Working Papers 14049.

Outreville, J. F., 2012, The Relationship between Insurance and Economic Development: 85 Empirical Papers for a Review of the Literature, Risk Management and Insurance Reivew, 1-52.

Pindyck, R.S., 1991. Irreversibility, Uncertainty, and Investment. Journal of Economic Literature 29, 1110–1148.

Pindyck, R.S. and A. Solimano, 1993, Economic instability and aggregate investment. In: Blanchard, O.J., Fischer, S. (Eds.), NBER Macroeconomics Annual 1993. MIT Press, Cambridge, MA, pp. 259–

Reinhart, C. M., and H.S. Rogoff, 2008, Banking Crises: An Equal Opportunity Menace, NBER Working Paper No. 14587.

Reinhart, C. M., and H.S. Rogoff, 2011, From Financial Crash to Debt Crisis, American Economic Review, 101(5), 1676-1706.

Rioja, F., F. Rios-Avila and N. Valev, 2012, The Persistent Effect of Banking Crises on Investment and the Role of Financial Markets, Working Paper, Georgia State University.

Truett, D. B., and L. J. Truett, 1990, The Demand for Life Insurance in Mexico and the United States: A Comparative Study, Journal of Risk and Insurance, 57(2), 321-328.

Ward, D. and R. Zurbruegg, 2000, Does Insurance Promote Economic Growth? Evidence from OECD Countries, Journal of Risk and Insurance, 67(4), 489-506.

Ward, D. and R. Zurbruegg, 2002, Law, Politics and Life Insurance Consumption in Asia, Geneva Papers on Risk and Insurance, 27, 365-412.

Zheng, W., Y. Liu, and Y. Deng, 2009, A Comparative Study of International Insurance Markets, Geneva Papers, 34, 85-99.

Zheng, W., Y. Liu, and G. Dickinson, 2008, The Chinese Insurance Market: Estimating its Long-Term Growth and Size, Geneva Papers, 33, 489-506.

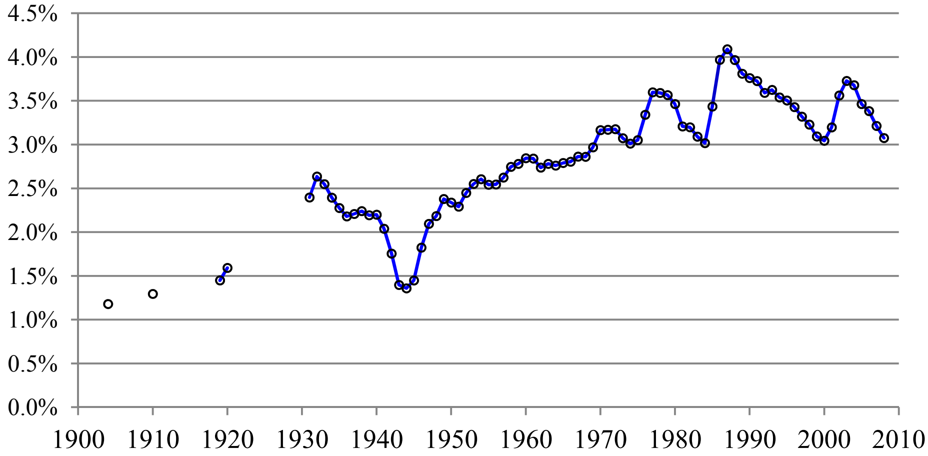
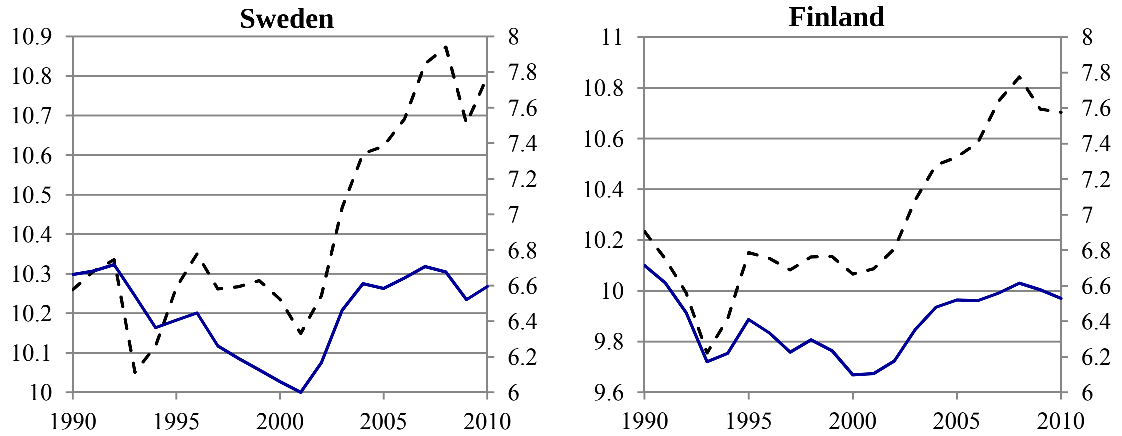
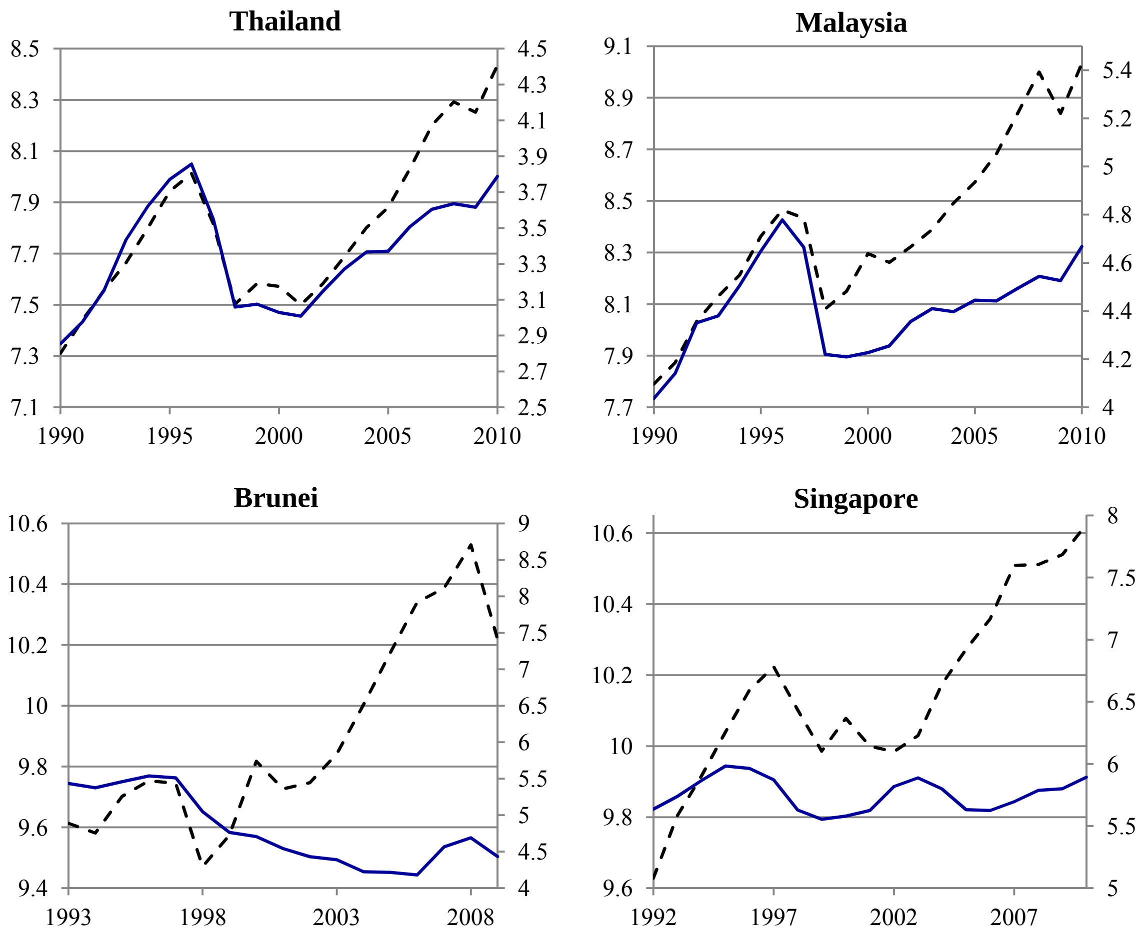


Figure 1 Non-life Insurance Premium Penetration (Premium as a % of GDP) in the US



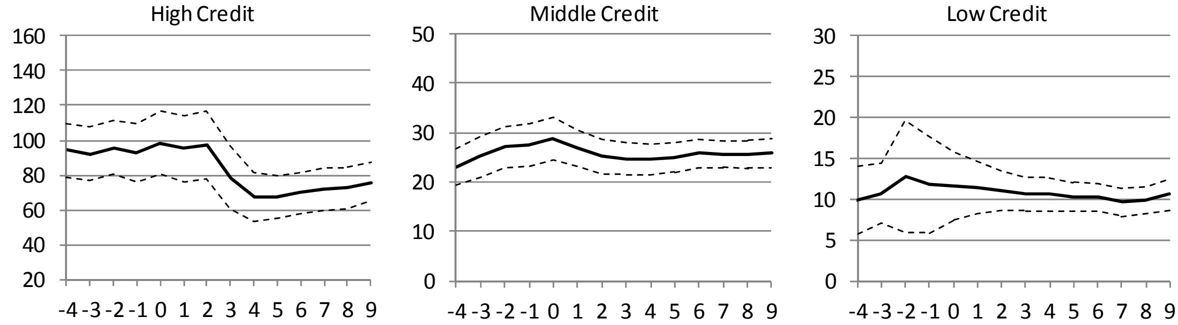
Dotted line: Log GDP per Capita (Left Axis)
Blue line: Log Non-life Premium per Capita (Right Axis)

Figure 2: Effect of Scandinavian Banking Crisis on Non-life Insurance Consumption



Dotted line: Log GDP per Capita (Left Axis)
Blue line: Log Non-life Premium per Capita (Right Axis)

Figure 3: Effect of Southeast Asian Crisis on Non-life Insurance Consumption



The time horizon represents years from a banking crisis in year 0. The line of each panel represents the mean of bank credit (% of GDP) and the dotted lines denote the 95 percent confidence interval.

Figure 4: The Level of Bank Private Credit

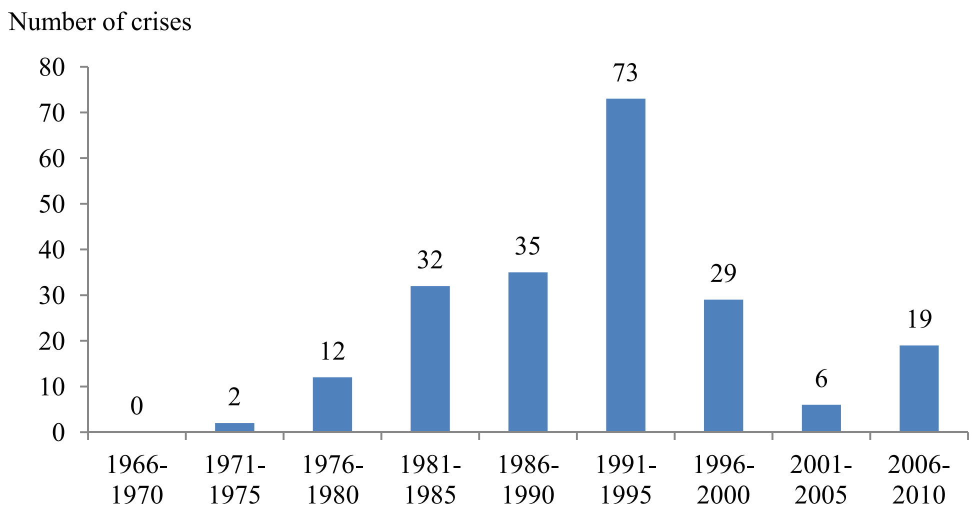


Figure 5: Frequency of Crisis Events

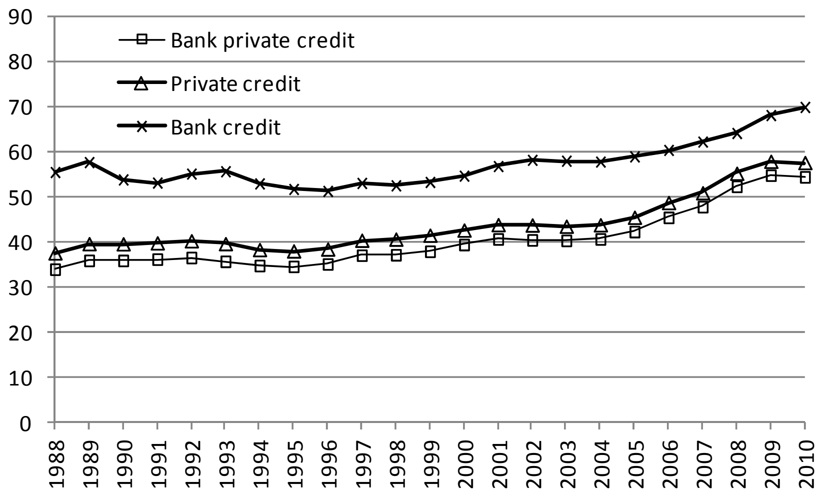


Figure 6: Trend of Credit Measures over Sample Period

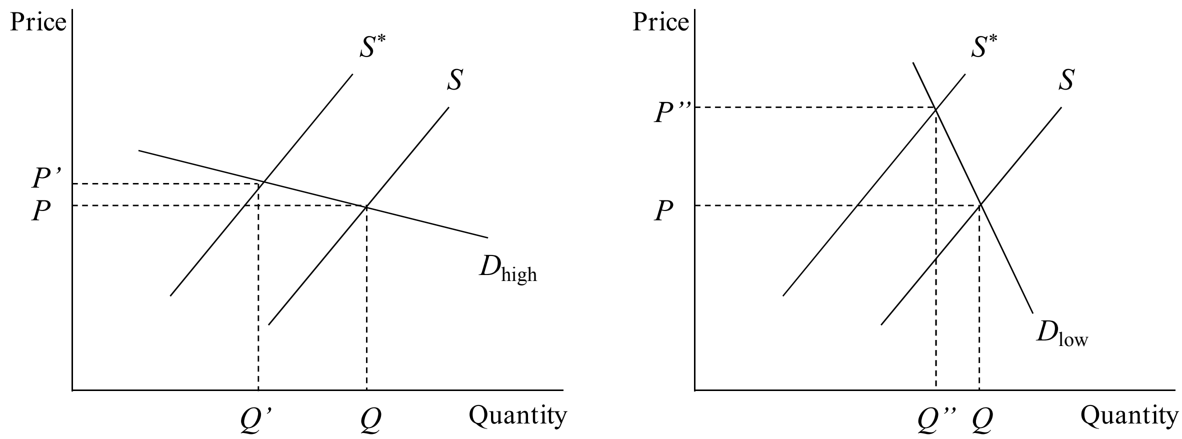


Figure 7: Effect of Supply Shock on Premium Volume

Table 1 Banking Crisis Variable Counts

Crisis variables	High Credit Countries	Middle Credit Countries	Low Credit Countries
Crisis	40	47	27
(% of Obs.)	(4.8%)	(5.2%)	(3.1%)
Crisis L1	42	52	32
Crisis L2	43	53	35
Crisis L3	34	52	36
Crisis L4	32	53	39
Crisis L5	36	53	41
Crisis L6	38	54	43
Crisis L7	38	58	44
Crisis L8	38	58	45
Crisis L9	39	56	46
Observation	837	901	860

Table 2 Definition of Variables

Variable	Definition	Source
Premium Penetration	Premium (nonlife, motor, property and liability) to GDP (%)	Axco; Swiss Re
Insurance Price	One-year lagged premium per loss (nonlife, motor, property and liability)	Axco
Bank Private Credit	Bank private credit to GDP (%)	World Bank
Private Credit	Private credit by deposit money banks and other financial institutions to GDP (%)	World Bank
Bank Credit	Domestic credit provided by banking sector to various sectors to GDP (%)	World Bank
Output	GDP per capita in 2010 US$	World Bank
Investment	Gross capital formation (% of GDP)	World Bank
Road Energy	Log of Road sector energy consumption per capita (kg of oil equivalent)	World Bank
Household Vehicle	Household final consumption expenditure on purchase of vehicles (% of GDP)	OECD.Stat

Table 3 Summary Statistics of Credit Measures by Country Classification

	Bank Private Credit			Private Credit			Bank Credit		
Country Group	Obs.	Mean	Std. Err.	Obs.	Mean	Std. Err.	Obs.	Mean	Std. Err.
High Credit	1186	81.5	1.3	1253	86.5	1.3	1381	106.2	1.4
Middle Credit	1103	28.0	0.4	1163	27.7	0.4	1211	42.0	0.6
Low Credit	1097	10.7	0.2	975	10.3	0.2	1196	15.8	0.4

Table 4 Variable Definition and Descriptive Statistics – By Bank Private Credit Classification

	High Credit Countries					Middle Credit Countries					Low Credit Countries				
	Obs	Mean	S.D.	Min	Max	Obs	Mean	S.D.	Min	Max	Obs	Mean	S.D.	Min	Max
Penetration															
Non-life	752	1.90	0.69	0.29	4.29	773	1.10	0.64	0.08	4.05	586	0.63	0.37	0.02	2.97
Motor Insurance	739	0.89	0.33	0.09	1.82	737	0.54	0.37	0.01	1.60	553	0.30	0.20	0.00	1.64
Property Insurance	741	0.48	0.28	0.03	1.37	759	0.32	0.28	0.02	2.57	577	0.14	0.10	0.00	0.86
Liability Insurance	586	0.23	0.18	0.00	0.92	492	0.09	0.11	0.00	0.60	346	0.06	0.08	0.00	0.57
Insurance Price															
Non-life	701	1.66	0.68	1.11	5.84	716	2.25	1.01	1.11	5.84	478	3.01	1.43	1.11	5.84
Motor Insurance	688	1.39	0.29	0.99	3.49	685	1.79	0.58	0.99	3.49	447	2.16	0.82	0.99	3.49
Property Insurance	696	2.14	1.20	0.94	12.4	701	3.35	2.53	0.94	12.4	473	4.73	3.31	0.94	12.4
Liability Insurance	549	2.48	2.84	0.93	25.0	471	4.76	4.15	0.93	23.9	277	4.66	4.06	0.93	25.2
GDP p.c. (2010 USD)	832	25992	18897	524	88163	867	4990	4740	326	24882	851	2007	2589	148	12037
Bank Private Credit	1186	81.5	43.5	9.47	434	1103	28.0	12.8	1.12	93.4	1097	10.7	7.41	0.12	65.2
Investment	1322	24.5	6.94	6.15	58.1	1189	22.4	6.85	6.11	61.5	1222	21.9	11.3	-0.69	114
Road Energy	1094	649	569	15.8	4880	996	248	277	3.27	2059	782	114	120	2.08	685
Household Vehicle Exp.	464	2.43	0.72	0.49	4.93	72	2.37	1.14	0.83	5.34	0	-	-	-	-

Table 5 Estimation: Non-life Penetration by Bank Private Credit Classification

The dependent variable is the penetration for non-life insurance total. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	High Credit		Middle Credit		Low Credit	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crisis	-0.011	-0.17	0.016	0.27	0.002	0.04
Crisis L1	-0.081	-1.21	0.029	0.54	0.001	0.02
Crisis L2	-0.092	-1.35	0.019	0.40	0.021	0.44
Crisis L3	-0.144 **	-2.58	0.026	0.51	0.030	0.57
Crisis L4	-0.101 *	-1.92	0.050	0.97	0.012	0.22
Crisis L5	-0.108 *	-1.72	0.039	0.77	-0.016	-0.32
Crisis L6	-0.066	-1.09	0.053	1.25	0.021	0.50
Crisis L7	-0.050	-0.89	0.086 **	2.27	0.020	0.59
Crisis L8	-0.050	-1.02	0.063 *	1.77	0.017	0.52
Crisis L9	-0.023	-0.61	0.040	1.32	0.012	0.47
Lagged Output	0.207	0.64	0.232	0.76	0.200	1.31
F-test for Crisis Dummies (p-value)	0.03		0.11		0.28	
F-test for Year Dummies (p-value)	0.00		0.00		0.09	
Countries	41		41		42	
Observations	733		730		575	
R squared	0.90		0.87		0.82	
Cummulative Crisis Effect	-0.73		0.42		0.12	

Table 6 Estimation: Non-life Penetration by Private Credit Classification

The dependent variable is the penetration for non-life insurance total. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	High Credit		Middle Credit		Low Credit	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crisis	-0.013	-0.20	0.012	0.22	0.008	0.14
Crisis L1	-0.083	-1.26	0.023	0.44	0.021	0.31
Crisis L2	-0.094	-1.40	0.016	0.34	0.028	0.52
Crisis L3	-0.144 **	-2.60	0.013	0.25	0.054	0.95
Crisis L4	-0.100 *	-1.90	0.036	0.72	0.034	0.58
Crisis L5	-0.107 *	-1.70	0.029	0.60	-0.007	-0.13
Crisis L6	-0.066	-1.08	0.049	1.23	0.019	0.41
Crisis L7	-0.050	-0.89	0.073 *	1.99	0.025	0.69
Crisis L8	-0.049	-1.00	0.055	1.63	0.020	0.57
Crisis L9	-0.022	-0.59	0.035	1.20	0.014	0.63
Lagged Output	0.183	0.59	0.282	0.92	0.187	1.25
F-test for Crisis Dummies (p-value)	0.03		0.39		0.26	
F-test for Year Dummies (p-value)	0.00		0.00		0.00	
Countries	42		43		39	
Observations	752		770		516	
R squared	0.91		0.86		0.86	
Cummulative Crisis Effect	-0.73		0.34		0.22	

Table 7 Estimation: Non-life Penetration by Bank Credit Classification

The dependent variable is the penetration for non-life insurance total. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	High Credit		Middle Credit		Low Credit	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crisis	0.019	0.33	-0.026	-0.39	0.055	1.08
Crisis L1	-0.049	-0.88	-0.001	-0.02	0.008	0.18
Crisis L2	-0.083	-1.41	0.010	0.17	0.027	0.57
Crisis L3	-0.135 ***	-2.88	0.002	0.03	0.043	0.95
Crisis L4	-0.086 *	-1.79	0.008	0.14	0.047	0.94
Crisis L5	-0.117 *	-1.90	0.016	0.30	-0.003	-0.07
Crisis L6	-0.076	-1.29	0.045	1.05	0.023	0.49
Crisis L7	-0.062	-1.10	0.058	1.68	0.051	1.07
Crisis L8	-0.060	-1.18	0.030	0.99	0.053	1.13
Crisis L9	-0.038	-0.98	0.037	1.53	0.022	0.60
Lagged Output	0.102	0.30	0.412	1.12	0.249 *	1.89
F-test for Crisis Dummies (p-value)	0.02		0.81		0.02	
F-test for Year Dummies (p-value)	0.00		0.00		0.00	
Countries	41		42		41	
Observations	754		727		557	
R squared	0.91		0.97		0.95	
Cummulative Crisis Effect	-0.69		0.18		0.32	

Table 8 Estimation: Non-life Penetration by Bank Private Credit Classification (Detrended)

The dependent variable is the penetration for non-life insurance total. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	High Credit			Middle Credit			Low Credit	
	Coef.		t-stat	Coef.		t-stat	Coef.	t-stat
Crisis	-0.016		-0.25	0.014		0.24	0.021	0.34
Crisis L1	-0.067		-1.00	0.012		0.24	0.006	0.09
Crisis L2	-0.095		-1.48	0.018		0.35	0.012	0.23
Crisis L3	-0.145	***	-2.76	0.032		0.61	0.017	0.28
Crisis L4	-0.103	**	-2.05	0.054		1.04	0.009	0.16
Crisis L5	-0.113	*	-1.90	0.046		0.91	-0.021	-0.39
Crisis L6	-0.073		-1.25	0.073	*	1.78	0.003	0.06
Crisis L7	-0.063		-1.18	0.106	***	2.94	0.010	0.26
Crisis L8	-0.061		-1.29	0.078	**	2.24	0.010	0.30
Crisis L9	-0.033		-0.90	0.055	*	1.86	0.004	0.14
Lagged Output	0.179		0.57	0.326		1.00	0.162	1.09
F-test for Crisis Dummies (p-value)	0.13			0.02			0.94	
F-test for Year Dummies (p-value)	0.00			0.00			0.16	
Countries	42			40			42	
Observations	763			697			578	
R squared	0.89			0.86			0.84	
Cummulative Crisis Effect	-0.77			0.49			0.07	

Table 9 Estimation: Non-life Density by Bank Private Credit Classification

The dependent variable is the logarithm of non-life insurance density (premium per capita). Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	High Credit			Middle Credit			Low Credit		
	Coef.		t-stat	Coef.		t-stat	Coef.		t-stat
Crisis	-0.049		-1.36	-0.049		-0.80	-0.030		-0.26
Crisis L1	-0.102	**	-2.65	-0.003		-0.06	-0.076		-0.68
Crisis L2	-0.092	**	-2.37	0.016		0.29	0.049		0.61
Crisis L3	-0.099	***	-2.83	0.048		0.81	-0.060		-0.56
Crisis L4	-0.067	**	-2.04	0.101	*	1.77	-0.139		-0.76
Crisis L5	-0.056		-1.51	0.091		1.59	-0.201		-1.20
Crisis L6	-0.032		-0.94	0.082	*	1.78	-0.081		-0.74
Crisis L7	-0.032		-1.04	0.113	**	2.65	-0.045		-0.65
Crisis L8	-0.035		-1.12	0.084	**	2.16	-0.041		-0.62
Crisis L9	-0.019		-0.80	0.041		1.17	-0.008		-0.17
Lagged Output	1.285	***	7.93	1.267	***	3.72	1.445	***	5.59
F-test for Crisis Dummies (p-value)	0.05			0.00			0.22		
F-test for Year Dummies (p-value)	0.00			0.00			0.01		
Countries	41			41			42		
Observations	733			730			575		
R squared	0.99			0.98			0.96		

Table 10 Estimation: Non-life Penetration by Swiss Re Sigma

The dependent variable is the non-life insurance penetration obtained from Swiss Re Sigma. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	High Credit		Middle Credit		Low Credit	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crisis	-0.016	-0.24	0.011	0.19	0.023	0.46
Crisis L1	-0.075	-1.13	0.025	0.50	0.016	0.23
Crisis L2	-0.082	-1.23	0.025	0.54	0.029	0.61
Crisis L3	-0.142 **	-2.63	0.039	0.75	0.027	0.54
Crisis L4	-0.110 **	-2.07	0.041	0.80	0.013	0.25
Crisis L5	-0.120 *	-1.93	0.039	0.77	-0.021	-0.44
Crisis L6	-0.086	-1.44	0.052	1.24	0.014	0.37
Crisis L7	-0.056	-1.01	0.078 **	2.04	0.017	0.52
Crisis L8	-0.073	-1.42	0.065 *	1.83	0.007	0.24
Crisis L9	-0.045	-1.04	0.041	1.34	0.009	0.39
Lagged Output	0.303	0.94	0.191	0.65	0.208	1.54
F-test for Crisis Dummies (p-value)	0.03		0.31		0.09	
F-test for Year Dummies (p-value)	0.00		0.00		0.43	
Countries	41		41		42	
Observations	730		732		620	
R squared	0.90		0.87		0.82	
Cummulative Crisis Effect	-0.81		0.42		0.13	

Table 11 Probit Model for the Probability of Banking Crisis (High Credit Countries)

The dependent variable is contemporaneous crisis variable. Results shown are from Probit regressions by income groups. All models include intercept. Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago.

	High Credit	
Parameter	Estimate	z-stat
Crisis L1	-5.454	0.00
Crisis L2	-0.317	0.53
Crisis L3	-0.156	0.11
Crisis L4	0.326	0.72
Crisis L5	-0.116	0.06
Crisis L6	-0.258	0.30
Crisis L7	-0.264	0.34
Crisis L8	-5.456	0.00
Crisis L9	-5.462	0.00
Laged Penetration	-0.010	0.00
Lagged Output	0.107	1.26
Observation	724	

Table 12 Model Estimation: Motor Insurance Penetration by Bank Private Credit Classification

The dependent variable is the penetration for non-life insurance total. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	Motor Insurance								
	High Credit			Middle Credit			Low Credit		
	Coef.		t-stat	Coef.		t-stat	Coef.		t-stat
Crisis	-0.077	**	-2.16	0.011		0.40	0.035		1.12
Crisis L1	-0.128	***	-3.17	-0.013		-0.50	0.030		0.77
Crisis L2	-0.143	***	-3.22	-0.019		-0.84	0.047		1.39
Crisis L3	-0.149	***	-4.19	-0.024		-1.00	0.028		0.83
Crisis L4	-0.122	***	-4.16	-0.024		-1.12	0.041		1.35
Crisis L5	-0.119	***	-3.90	-0.027		-1.50	0.026		0.88
Crisis L6	-0.099	***	-3.59	-0.012		-0.75	0.041		1.46
Crisis L7	-0.075	***	-3.09	0.009		0.52	0.031		1.15
Crisis L8	-0.060	**	-2.43	0.015		1.02	0.029		1.25
Crisis L9	-0.040	*	-1.87	0.003		0.20	0.024		1.33
Lagged Output	0.063		0.27	0.337	**	2.17	0.164	**	2.50
F-test for Crisis Dummies (p-value)	0.00			0.16			0.39		
F-test for Year Dummies (p-value)	0.00			0.01			0.00		
Countries	41			40			40		
Observations	722			695			543		
R squared	0.90			0.91			0.98		
Cummulative Crisis Effect	-1.01			-0.08			0.33		

Table 13 Model Estimation: Property Insurance Penetration by Bank Private Credit Classification

The dependent variable is the penetration for non-life insurance total. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	Property Insurance					
	High Credit		Middle Credit		Low Credit	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crisis	0.014	0.77	0.002	0.07	-0.015	-0.69
Crisis L1	0.009	0.43	0.021	0.81	-0.012	-0.54
Crisis L2	0.007	0.40	0.031	0.99	-0.012	-0.71
Crisis L3	-0.013	-0.76	0.030	0.83	-0.001	-0.08
Crisis L4	-0.015	-0.94	0.042	1.08	-0.004	-0.25
Crisis L5	-0.023	-1.47	0.033	0.81	-0.009	-0.57
Crisis L6	-0.016	-1.08	0.002	0.08	-0.008	-0.58
Crisis L7	-0.022	-1.55	0.013	0.73	-0.017	-1.56
Crisis L8	-0.018	-1.25	0.011	0.68	-0.011	-1.17
Crisis L9	-0.008	-0.66	0.025	1.36	-0.015 **	-2.38
Lagged Output	-0.116	-1.46	-0.156	-0.98	-0.027	-0.53
F-test for Crisis Dummies (p-value)	0.08		0.44		0.22	
F-test for Year Dummies (p-value)	0.00		0.00		0.00	
Countries	41		41		41	
Observations	723		724		567	
R squared	0.95		0.73		0.78	
Cummulative Crisis Effect	-0.09		0.21		-0.11	

Table 14 Model Estimation: Liability Insurance Penetration by Bank Credit Classification

The dependent variable is the penetration for non-life insurance total. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	Liability Insurance					
	High Credit		Middle Credit		Low Credit	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crisis	-0.002	-0.12	-0.004	-0.46	-0.032	-1.37
Crisis L1	-0.008	-0.44	-0.005	-0.89	-0.027	-1.66
Crisis L2	-0.020	-1.08	0.003	0.57	-0.041	-1.48
Crisis L3	-0.019	-0.93	0.006	1.38	-0.038	-1.49
Crisis L4	0.003	0.16	0.011 **	2.39	-0.040	-1.54
Crisis L5	0.008	0.42	0.017 ***	3.00	-0.020	-1.11
Crisis L6	0.005	0.34	0.014 **	2.54	-0.013	-0.82
Crisis L7	0.005	0.32	0.015 **	2.28	-0.011	-1.06
Crisis L8	0.003	0.27	0.004	0.79	-0.016	-1.50
Crisis L9	-0.006	-0.58	0.003	0.72	0.004	0.54
Lagged Output	-0.115 *	-1.80	-0.046	-1.01	0.011	0.25
F-test for Crisis Dummies (p-value)	0.88		0.33		0.05	
F-test for Year Dummies (p-value)	0.00		0.00		0.00	
Countries	38		34		34	
Observations	574		465		338	
R squared	0.90		0.94		0.82	
Cummulative Crisis Effect	-0.03		0.06		-0.23	

Table 15 Model Estimation: Non-life Penetration by Income Countries

The dependent variable is the penetration for non-life insurance total. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	Non-life Aggregate											
	High			Upper-Middle			Lower-Middle			Low		
	Coef.		t-stat	Coef.		t-stat	Coef.		t-stat	Coef.		t-stat
Crisis	-0.019		-0.27	0.003		0.06	0.055		1.5	-0.112		-1.26
Crisis L1	-0.104		-1.30	-0.050		-1.06	0.058	*	1.93	0.003		0.03
Crisis L2	-0.151	**	-2.17	-0.029		-0.65	0.049		1.69	0.015		0.20
Crisis L3	-0.249	***	-3.45	-0.031		-0.61	0.081	**	2.52	-0.009		-0.11
Crisis L4	-0.192	***	-2.52	0.001		0.02	0.101	***	2.95	-0.079		-0.82
Crisis L5	-0.194	**	-2.33	0.000		0.01	0.076		1.62	-0.102		-1.00
Crisis L6	-0.122		-1.55	0.060		0.98	0.048	*	1.89	-0.082		-0.97
Crisis L7	-0.070		-0.94	0.071		1.19	0.052	**	2.23	-0.033		-0.44
Crisis L8	-0.061		-1.02	0.058		1.05	0.032		1.26	0.014		0.21
Crisis L9	-0.020		-0.49	0.036		0.82	0.008		0.34	0.043		0.98
Lagged Output	-0.418		-0.72	0.455	**	2.43	0.135		0.82	0.616	**	2.29
F-test for Crisis Ds (p-value)	0.03			0.06			0.00			0.00		
F-test for Year Ds (p-value)	0.00			0.00			0.00			0.00		
Number of Countries	34			36			31			23		
Observations	647			595			498			298		
R squared	0.90			0.87			0.89			0.89		
Cummulative Crisis Effect	-1.18			0.12			0.56			-0.34		

Table 16 Motor Insurance Penetration by Income Groups

The dependent variable is motor insurance penetration. Results shown are from robust fixed effects regressions by income groups. All models include intercept, country fixed-effects, and year dummy variables (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	Motor Insurance											
	High			Upper-Middle			Lower-Middle			Low		
	Coef.		t-stat	Coef.		t-stat	Coef.		t-stat	Coef.		t-stat
Crisis	-0.089	**	-2.27	-0.002		-0.06	0.035	*	1.78	-0.048		-1.07
Crisis L1	-0.161	***	-3.61	-0.046		-1.39	0.027		1.22	0.000		0.00
Crisis L2	-0.177	***	-3.80	-0.042		-1.48	0.024		1.08	-0.005		-0.11
Crisis L3	-0.198	***	-4.79	-0.057	**	-2.20	0.019		0.96	0.012		0.26
Crisis L4	-0.168	***	-4.46	-0.038		-1.41	0.023		1.26	-0.029		-0.69
Crisis L5	-0.152	***	-4.17	-0.041		-1.58	0.011		0.72	-0.048		-0.89
Crisis L6	-0.104	***	-3.49	-0.019		-0.71	0.014		0.96	-0.060		-1.17
Crisis L7	-0.070	**	-2.28	-0.012		-0.43	0.016		1.16	-0.044		-0.96
Crisis L8	-0.042		-1.50	-0.010		-0.38	0.003		0.20	0.001		0.03
Crisis L9	-0.024		-1.04	-0.015		-0.73	-0.008		-0.63	0.025		1.12
Lagged Output	-0.173		-0.78	0.355	**	2.15	0.177		1.59	0.119		1.09
F-test for Crisis Ds (p-value)	0.00			0.07			0.26			0.00		
F-test for Year Ds (p-value)	0.00			0.00			0.00			0.00		
Countries	34			36			30			21		
Observations	645			568			461			286		
R squared	0.92			0.97			0.92			0.90		
Cummulative Crisis Effect	-1.19			-0.28			0.17			-0.20		

Table 17 Estimation: Insurance Price Effect

The dependent variable is motor insurance penetration. Results shown are from robust fixed effects regressions. All models include intercept, country fixed-effects (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	High Credit		Middle Credit		Low Credit	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crisis	-0.018	-0.31	0.091 *	1.85	0.033	0.50
Crisis L1	-0.067	-1.02	0.076	1.62	0.024	0.30
Crisis L2	-0.111	-1.48	0.064 *	1.73	0.009	0.12
Crisis L3	-0.158 ***	-2.75	0.082 *	1.84	0.085	1.24
Crisis L4	-0.131 **	-2.57	0.077 *	1.70	0.051	0.84
Crisis L5	-0.091 *	-1.80	0.065	1.39	0.010	0.16
Crisis L6	-0.098	-1.55	0.064	1.59	0.044	0.89
Crisis L7	-0.066	-1.08	0.047	1.55	0.052	1.36
Crisis L8	-0.065	-1.26	0.056 *	1.74	0.030	0.79
Crisis L9	-0.044	-0.93	0.042	1.38	0.000	0.00
Lagged Output	0.073	0.17	0.559 ***	2.75	0.157	0.82
Insurance Price	-0.027	-0.87	0.034	1.15	-0.004	-0.34
F-test for Crisis Dummies (p-value)	0.06		0.27		0.00	
F-test for Year Dummies (p-value)	0.00		0.00		0.00	
Countries	40		40		38	
Observations	658		644		440	
R squared	0.89		0.90		0.82	
Cummulative Crisis Effect	-0.85		0.66		0.34	

Table 18 Estimation: Investment and Credit Effects in High Bank Private Credit Countries

The dependent variable is non-life insurance penetration. Results shown are from robust fixed effects regressions. All models include intercept, country fixed-effects (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	(1)		(2)		(3)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crisis	-0.025	-0.51	0.001	0.01	-0.007	-0.16
Crisis L1	-0.089	-1.60	-0.071	-1.03	-0.093	-1.61
Crisis L2	-0.136 **	-2.03	-0.102	-1.29	-0.128 *	-1.82
Crisis L3	-0.161 ***	-2.96	-0.174 **	-2.46	-0.178 **	-2.67
Crisis L4	-0.128 **	-2.46	-0.145 **	-2.60	-0.142 **	-2.59
Crisis L5	-0.089 *	-1.70	-0.103 *	-1.99	-0.101 *	-1.91
Crisis L6	-0.094	-1.44	-0.106 *	-1.70	-0.102	-1.59
Crisis L7	-0.064	-1.02	-0.074	-1.20	-0.071	-1.13
Crisis L8	-0.064	-1.20	-0.069	-1.38	-0.068	-1.31
Crisis L9	-0.041	-0.84	-0.049	-1.05	-0.046	-0.96
Lagged Output	0.055	0.14	0.058	0.14	0.040	0.10
Insurance Price	-0.026	-0.84	-0.023	-0.77	-0.023	-0.73
Private Bank Credit	0.000	0.22			0.000	0.27
Investment			-0.002	-0.33	-0.003	-0.36
Countries	40		40		40	
Observations	638		657		637	
Cummulative Crisis Effect	-0.89		-0.89		-0.94	

Table 19 Estimation: Exposure Effects in High Bank Private Credit Countries

The dependent variable is motor insurance penetration. Results shown are from robust fixed effects regressions. All models include intercept, country fixed-effects (not reported). Crisis L*k*.is a dummy variable for a banking crisis that occurred *k* years ago. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at 10 percent by robust standard errors.

	(1)			(2)			(3)		
	Coef.		t-stat	Coef.		t-stat	Coef.		t-stat
Crisis	-0.093	**	-2.55	-0.078	**	-2.15	-0.076	**	-2.23
Crisis L1	-0.125	***	-3.06	-0.134	***	-2.88	-0.130	***	-2.88
Crisis L2	-0.154	***	-3.36	-0.175	***	-4.05	-0.173	***	-3.99
Crisis L3	-0.174	***	-4.14	-0.241	***	-5.30	-0.239	***	-5.31
Crisis L4	-0.153	***	-4.55	-0.218	***	-6.06	-0.218	***	-6.11
Crisis L5	-0.138	***	-4.62	-0.171	***	-5.42	-0.172	***	-5.56
Crisis L6	-0.122	***	-3.70	-0.147	***	-4.61	-0.149	***	-4.57
Crisis L7	-0.085	***	-2.81	-0.099	***	-2.98	-0.102	***	-3.11
Crisis L8	-0.066	**	-2.26	-0.057	*	-1.83	-0.060	*	-1.98
Crisis L9	-0.042		-1.56	-0.028		-1.06	-0.032		-1.23
Lagged Output	-0.167		-0.69	-0.205		-0.89	-0.321		-1.20
Insurance Price	-0.029		-0.44	0.060		0.84	0.048		0.71
Road Energy Consumption	0.102		1.66				0.152		1.18
Household Vehicle Expenditure				-0.006		-0.18	-0.009		-0.27
Countries	39			22			22		
Observations	626			360			360		
Cummulative Crisis Effect	-1.15			-1.35			-1.35		