Adverse Selection and Moral Hazard in Corporate Insurance Markets: Evidence from the 2011 Thailand Floods*

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Abstract

This paper is the first empirical study on adverse selection and moral hazard in the corporate disaster insurance market. By constructing and examining a unique plant-level panel dataset on the 2011 Thailand floods, we overcome the general lack of data that has previously prevented a systematic study on the issue. By exploiting unexpected, large losses caused by a severe disaster, we find evidence of adverse selection for both property and business interruption insurance. Moral hazard, measured by impacts on recovery efforts, is also found for both types of insurance, albeit more salient effects for business interruption insurance.

Keywords: Adverse selection; business interruption insurance; moral hazard; property insurance.

JEL classifications: D82, G22, H84

1 Introduction

Extreme events such as natural disasters and the COVID-19 pandemic have increasingly been hitting various regions in the world recently (CRED, 2019; IFRC, 2020). Yet, in general, losses from disasters are not very well protected financially. According to Swiss Re Institute (2021), globally in 2020 only 81 billion US dollars were covered by insurance out of 190 billion US dollars of economic losses from natural disasters, leaving a gap of more than 100 billion US dollars. It is therefore important to uncover the mechanism that causes the low penetration of disaster insurance.

There is a large literature that addresses the issue of low penetration in the context of household disaster insurance. Kunreuther et al. (1978) is among the first that reported the phenomenon, and there are both theoretical and empirical studies that attempt to uncover the mechanism causing the low insurance penetration: For instance, Camerer and Kunreuther (1989) reviews possible causes on the demand side, and more recent studies include Browne and Hoyt (2000), Kriesel and Landry (2004), Bin et al. (2008), Michel-Kerjan et al. (2012), Botzen and van den Bergh (2012), Gallagher (2014) and Mol et al. (2020).

By contrast, the empirical literature on corporate demand for insurance is limited, not just on the issue of low penetration of disaster insurance, but more generically. Zou et al. (2003), Adams et al. (2011), Michel-Kerjan et al. (2015), and Asai (2019) are among the few studies that empirically examine corporate demand for insurance, yet none of them directly examines the causes of low disaster insurance penetration or market failures.

Very limited access to firm-level (or plant-level) data that contain both insured and uninsured firms has made empirical studies on corporate insurance difficult. The data available to researchers are typically those collected by insurance companies, which lack the uninsured firms.[1] It is therefore not straightforward to empirically address issues related to market failures in corporate insurance markets by using observational firm data.

In order to overcome the general lack of data that include firms not subscribing to any insurance policy, we collected data on our own from both insured and uninsured plants in central Thailand, exploiting a peculiar situation that may be understood as a natural experiment, the 2011 Thailand floods. Starting in July 2011, Thailand was hit by massive floods along the Chao Phraya river basin, first in northern and northeastern provinces, and later in the central part of the country, where major industrial estates and/or parks are located. A large proportion of plants were inundated at a level the region had not experienced previously, and their operations were widely disrupted. As mentioned above, the data we collected include both inundated and non-inundated plants in central Thailand with the latter located outside the Chao Phraya river basin. We first show that the non-insurance related plant (or firm) characteristics between those located in the flooded areas and those in the non-flooded areas are comparable a priori, corroborating that the severity of floods was unexpected ex ante, and the level of losses that the plants in the flooded areas incurred is arguably random.

Information asymmetry, such as adverse selection or moral hazard, may undermine proper functioning of the insurance market, i.e., market failures. On one hand, riskier

[1] Enterprise surveys usually do not include questions on insurance and corporate financial statements include only very limited information on insurance.

agents are more likely to subscribe to insurance (i.e., adverse selection), leading to higher premiums or costly contracts. It is well known that adverse selection may lead to a complete collapse of the insurance market (Rothschild and Stiglitz, 1976). On the other hand, *ex post* moral hazard may arise in the form of false claims because of difficulties in verification (Chiappori and Salanié, 2013).[2] That is, insurance payment may loosen the financial constraint in the short-run, and gives the insured reduced incentives to recover more quickly. Hence, we hypothesize and empirically test if such market failures indeed exist in corporate disaster insurance markets.

It is nevertheless important to pay attention to the difference between corporate and household insurance markets, since corporate motives for insurance subscription are said to be different from household motives in the literature — in particular, the risk aversion motive is not applicable to firms because investors can diverse risk better and cheaper than firms do (Mayers and Smith, 1982; Hoyt and Khang, 2000). One main corporate motive for insurance subscription arises from bankruptcy costs, which include costs arising from various agency problems that reflect conflicts of interest between different stakeholders, and opportunity costs of lost techniques and/or know-hows.[3] Firms therefore try to protect themselves financially against extreme events leading to bankruptcy by subscribing to insurance policies. De Mel et al. (2012) finds empirically that availability of financial support plays a critical role in achieving businesses' timely recovery from disasters, suggesting potential benefits of corporate disaster insurance consistent with the bankruptcy costs motive. Also, Dong and Tomlin (2012) theoretically examines business interruption (BI) insurance and operational measures including inventory as management strategies against business disruption risks, and shows that BI insurance and operational measures are not always substitutes, but may function as complements.

To preview, we find evidence that is consistent with the existence of both adverse selection and moral hazard for both property and BI insurance. Firms located in the

[2]By contrast, *interim* moral hazard refers to reduced incentives for prevention, which may arise because of smaller benefits of prevention efforts upon insurance subscription.

[3]Other corporate motives for insurance subscription usually include tax effects, benefits from real services by insurers, the regulatory environment and other agency problems (e.g., underinvestment problems), although these are not the main focus in the current paper.

flooded areas were more likely to subscribe to insurance before the 2011 floods. After the 2011 floods, fewer of these firms are subscribing to insurance. These findings are consistent with the existence of adverse selection, since the 2011 floods may have tightened the supply of insurance. We also find that firms that receive insurance payments tend to exert less effort to recover their operation: They tend to produce less, to hire fewer workers, and to take more time to resume operation. These are consistent with *ex post* moral hazard for both types of insurance, albeit more salient effects for business interruption insurance.

While there are empirical studies that examine adverse selection and/or moral hazard in the context of household insurance (Abbring et al., 2003; Cohen and Siegelman, 2010; Hudson et al., 2017; Wagner, 2022), to the best of our knowledge there is no existing study that directly examines adverse selection and/or moral hazard in corporate insurance markets empirically. The current paper fills this important gap in the literature.

The rest of the paper proceeds as follows. Section 2 briefly describes the 2011 Thailand floods, and then the data and variables used in the current paper including their descriptive statistics. Section 3 explains the econometric strategy to test the existence of adverse selection and moral hazard in the corporate property and business interruption insurance markets. Section 4 reports the results of the empirical tests and discusses the implications of the findings, and Section 5 concludes the paper.

2 Background and Data

In this section, we begin by explaining our quasi-experimental setting, the 2011 Thailand floods, and some classifications that measure preparedness for large adverse events in the corporate sector that are relevant to our analysis. We then describe the sources of data that are used in the subsequent empirical analyses.

2.1 The 2011 Thailand Floods

We first explain the timeline of the 2011 Thailand floods. Tropical Storm Nock-ten brought heavy rainfalls in northern and northeastern provinces in Thailand from July 31,

2011. In October 2011, the lower Chao Phraya basin was hit by severe floods. The floods were caused by heavy monsoon rains in all regions along the Chao Phraya River – not only in the lower basin itself, but also in the upstream regions. The 2011 floods were indeed the worst in the past five decades: The estimated total losses amounted to THB 1,425 billion or 45.7 billion USD, with the manufacturing sector most severely hit at total losses of THB 1,007 billion or 32 billion USD (World Bank, 2011). The floods showed us that unexpected, severe adverse events could occur in Thailand, an otherwise steadily growing middle income country.[4] This may manifest itself the importance of protection against floods, including formal insurance schemes, for an emerging economy to achieve stable and sustainable growth.

It is also worth emphasizing that the floods did not hit the whole country but only its particular region (the Chao Phraya basin). As we describe in detail in the data section, we will exploit this feature to create treatment and control groups in the empirical analysis.

2.2 Types of Corporate Insurance Policies

Insurance policies offered to firms include those that cover losses or damages to buildings, equipment and infrastructure, and those that cover loss of earnings or profits from business interruptions. Business interruptions may arise from direct damages to the firm's properties, but may also arise indirectly from damages to other firm's properties through the supply chain. Indirectly caused business interruptions therefore provide firms with different motives for insurance coverage from motives for coverage against direct losses.

As Rose and Huyck (2016) explains, business interruption (BI) insurance is usually sold as an additional policy provision to standard property and casualty insurance, and the period of disruption is defined as the lesser of the actual or theoretical time to repair, rebuild, or replace the damaged property, or the time to relocate permanently. Although the insured is supposed to conduct due diligence in mitigating losses, it is an empirical

[4]From the perspective of meteorological studies, Promchote et al. (2016) analyses the cause of the 2011 floods. Their attribution analysis points out that anthropogenic greenhouse gases may cause substantially increased rainfall, which could further increase the flooding risk in the future.

question to test if this is indeed the case. BI insurance payments are usually based on the actual loss of earnings or profits. Policies covering only loss of earnings stop paying as soon as the insured's business resumes, while those with more extensive coverage continue paying until the insured's business recovers to a normal level subject to the maximum period of indemnity. Either way, the insurance coverage may give perverse incentives to the insured firms so that recovery efforts may be reduced.

To simplify the exposition in the current paper, property insurance means insurance coverage for direct/physical losses or damages to the plant, and business interruption insurance means insurance coverage for indirect losses due to business interruptions, both definitions corresponding to the data used.

In addition to subscriptions to insurance policies, some firms draw up a business continuity plan (BCP) so as to prepare for possible adverse events. BCPs aim at helping firms minimize damage, continue their operations, and achieve quicker recovery from disasters or other emergencies. BCPs are supposed to be effective in improving preparedness against extreme tail events that are uninsurable, while firms may only purchase insurance if the perceived risk is insurable. For example, if a firm expects that a significant negative event is likely, it develops a BCP to minimize the damage that the event would cause. In the following section, we will show that firms in the flooded area and non-flooded area are balanced in the sense of BCP development, suggesting that firms in the flooded area did not expect an extreme tail event any more than those in the non-flooded areas.

2.3 Data

This paper employs matched panel data, comprising financial panel data from Orbis Bureau van Dijk (BvD, hereafter) database between 2010 and 2012 and micro data of Japanese overseas subsidiary plants operating in central Thailand from the 'RIETI Survey of Industrial Estates/Parks and Firms in Thailand on Geographic and Flood Related Information' (the RIETI survey hereafter) conducted by Teikoku Data Bank (TDB) from

October 2013 until January 2014.[5] While the data collected by the RIETI survey are retrospective, Orbis BvD data are collected contemporaneously; thus, concerns over possible biases arising from retrospectively collected data are mitigated.

The RIETI survey has two modules: Plant-level module and Industrial Estate/Park (IE/IP) operator module, and its data were collected by two methods – a postal survey in Japan and a survey in Thailand, which was conducted in cooperation with the Industrial Estate Authority of Thailand (IEAT). The postal questionnaire in Japan was sent to 842 plants selected from TDB's database. The selection criteria were plant size in terms of annual turnover (at least two billion yen), number of employees (at least 50), and presence in Thailand. The survey in Thailand targeted plants operating in 34 major IEs/IPs in central Thailand (in Ayutthaya, Bangkok, Chachoengsao, Chonburi, Pathum Thani, Prachinburi, Rayong, Samut Prakan, and Saraburi provinces) and their operators.[6] There are plants that did not locate in any major IEs/IPs, which are located geographically distant from each other. Therefore, in the following regression analysis, these plants are treated as separate clusters. As a result, we have 65 separate clusters for computing cluster-robust standard errors.

Among the plant-level module data and IE/IP operator module data, the current study uses the former module, which consists of four sections. The first section focuses on basic attributes of the respondent's plant, such as location, plant size, and operation history, the second section is dedicated to flood-related information, such as direct/indirect losses from floods and inundation experience in the past and past and present risk perceptions towards floods. The third section asks insurance-related questions, including the subscription status of property and business interruption insurance before and after the 2011 floods, insurance payment receipt status and month of receipt. The final section is on business-related questions, such as past and present main trading partners, past and present business sentiment, workforce size, wage and bonus payments, recruitment conditions, and labour disputes.

[5]TDB was commissioned by the Research Institute of Economy, Trade and Industry (RIETI) to conduct the survey.

[6]Table A.1 in the online appendix list the 34 IEs/IPs.

In total, 314 plants responded to the plant questionnaire: 129 responses were collected through the postal questionnaire sent to head offices of the parent companies in Japan, and 185 responses were collected from the survey in Thailand, of which 102 responses were collected through face-to-face interviews, 38 through postal questionnaire, and 45 by telephone interviews. In order to maintain consistency as well as for a cleaner interpretation, we dropped plants that changed location after the 2011 floods from the samples used in the current paper.[7] This procedure leaves us with 300 plants within our sample. The samples spread geographically so that statistically meaningful comparisons may be done between areas that suffered from heavy losses and areas otherwise. In particular, among surveyed provinces, Ayutthaya and Pathum Thani provinces had many plants that reported severe damage or losses from floods.[8]

As noted before, the data from the RIETI survey are matched with financial data from Orbis BvD dataset. Orbis BvD collects financial data for more than 200 million companies in the world as of 2018 (Kalemli-Ozcan et al., 2015). From Orbis BvD data, we obtain variables such as total assets, solvency ratio, revenues, and net income for years 2010, 2011, 2012. We merge the RIETI survey with Orbis BvD by company name and by location. This procedure yields several non-matched companies, which results in 289 matched plants in the RIETI-Orbis BvD-merged dataset. We flag the remaining non-matched plants and keep them in the regression analysis.

2.3.1 Descriptive Statistics

We report the summary statistics in Table 1. Panel A presents insurance related variables, including insurance subscription before and after the 2011 floods and insurance payment after the 2011 floods. We find that insurance penetration was 36% for property insurance and 16% for BI insurance in 2011 before the floods. In 2013, insurance penetration fell to 28% and 8%, respectively. More than half of the plants that had had insurance coverage

[7]Although there is risk of selection bias in accord with location choice, such a concern is of secondary importance, given that the number of plants that changed the location after the floods is small, i.e. 14.

[8]Figure A.1 in the online appendix shows the provinces in central Thailand, where the plants the RIETI survey studied are located, Figure A.2 the sample size for each province, Figures A.3 and A.4 the maximum number of inundation days and depth of inundation, respectively.

before the 2011 floods received at least some insurance payments against their claims for both types of insurance, but insurance payments tended to take longer for property insurance than for BI insurance. This is consistent with the nature of the two types of insurance policies; property insurance is paid out only after the losses are verified, and such verification process may be costly and lengthy, while BI insurance is designed so that payments are made quickly by eliminating the lengthy verification process.

Panel B reports descriptive statistics of variables related to firm performance and/or operations. For both production and employment variables, we find that the plants located in Ayutthaya and Pathum Thani (AP) provinces were less likely to increase the scale of their operations after the floods. Also, the plants located in Ayutthaya and Pathum Thani provinces suspended their operations for a longer period than those located elsewhere. This suggests that severe flood damage or losses prevented firms located in AP provinces from a quick recovery.

One may argue that there are systematic differences in the (ex ante) characteristics of the plants between the those located in AP provinces and those located elsewhere. To alleviate such concerns, we perform a balancing test that verifies if the two groups are different only in insurance subscription. To this end, we examine BCP setup status, plant characteristics, and corporate financial characteristics. 'BCP status' is a variable that indicates if the firm developed the BCP before (and after) the 2011 floods and this variable is supposed to measure preparedness for severe adverse events. Plant characteristics to be tested include an indicator if the plant is multi-storey, an indicator if the equipment is above the ground floor, and log floor areas. They have impacts on the benefits of insurance subscription, since the size and the likeliness of property losses are affected by them. The financial measures included are pre-floods log asset, solvency ratio, log revenue and log net income. Pre-floods log asset and log revenue represent the firm size, and solvency ratio and log net income correspond to profitability of the firm. Note that both firm size and profitability are likely to be related to the tightness of credit constraints. In Panel C, we compare the means of these variables between the two groups, i.e. AP and the

Table 1: Summary Statistics

Panel A: Descriptive Statistics – Insurance

	Mean	Stdev.	Min	Median	Max	N
Property Ins. 2011	0.360	0.481	0	0	1	300
Property Ins. 2013	0.277	0.448	0	0	1	300
Bus. Int. Ins. 2011	0.160	0.367	0	0	1	300
Bus. Int. Ins. 2013	0.0833	0.277	0	0	1	300
PI Paid Dummy	0.243	0.430	0	0	1	300
PI Payment Delay (*Delay*)	4.315	6.547	0	0	20	73
BI Paid Dummy	0.110	0.313	0	0	1	300
BI Payment Delay (*Delay*)	2.333	5.560	0	0	20	33

Panel B: Descriptive Statistics – Other Firm Performances

	Location	No production	Decreased	Constant	Increased	Missing	Total
Production	AP	4	30	19	44	6	103
(ΔY)	Elsewhere	4	25	40	105	23	197
	Total	8	55	59	149	29	300
Worker	AP		30	28	33	12	103
Employment	Elsewhere		24	34	93	46	197
(ΔL)	Total		54	62	126	58	300

	(months)	0	1	2	3	4	5/6	Longer	Missing	Total
Length of	AP	1	28	29	19	8	9	7	2	103
Suspension	Elsewhere	122	10	1	0	1	0	1	62	197
(RT)	Total	123	38	30	19	9	9	8	64	300

	Mean	Std. Dev.	Min	Max	N
Losses (million USD)	6.959	55.28	0	917.5	300
Assets (million USD)	3.360	29.39	0	481.7	300

Panel C: Balancing Test

	AP	Elsewhere	Difference	Std. Err.	t-value
Pre- and Post-Floods BCP Setup Status					
BCP introduced before the 2011 floods	0.0291	0.0305	-0.00133	(0.0208)	0.0639
BCP introduced after the 2011 floods	0.214	0.0203	0.193***	(0.0324)	5.957
N			300		
Pre-2011-Floods Plant Characteristics					
Multi-storey building	0.351	0.339	0.0114	(0.0604)	0.189
Equipment above ground floor	0.0444	0.0592	−0.0147	(0.0296)	−0.497
log floor area (sq. meters)	9.232	9.659	−0.427	(0.289)	−1.480
N			277[†]		
Pre-2011-Floods Corporate Financial Characteristics					
Assets 2010 (in natural logarithm)	6.108	6.154	−0.0459	(0.254)	−0.181
Solvency ratio 2010	52.82	57.86	−5.043	(4.732)	−1.066
Revenue 2010 (in natural logarithm)	6.191	6.329	−0.138	(0.340)	−0.405
Net income 2010 (in natural logarithm)	3.454	3.604	−0.150	(0.385)	−0.388
N			162[†]		

Notes: Data are from the RIETI and RIETI-Orbis BvD-merged datasets. In Panel A, 'Months of Delay' are calculated from October 2011, and are defined for only firms that have answered that they have received the insurance payment. Panel B reports the distribution of firm performance variables such as the changes in production and worker employment before and after the floods. AP stands for Ayutthaya and Pathum Thani. Monetary values are in recorded in million THB and converted into 2011 million USD using the FRED database (https://fred.stlouisfed.org/series/AEXTHUS). In Panel C, 'Multi-storey building' indicates non-single storey building, and 'Equipment above ground floor' means production equipment is placed above the ground floor. [†]23 firms did not answer RIETI survey's equipment questions. 138 firms did not match Orbis-BvD database or did not report financial variables. *** p<0.01, ** p<0.05, * p<0.1.

rest, and do not find 10% statistically significant differences, except four 'BCP introduced after the 2011 floods'.[9] This result implies that the plants are balanced between flooded and non-flooded locations.

3 Econometric Strategy

First an empirical specification that leverages the unique feature of the RIETI survey will be presented, followed by the summary of existing theoretical predictions about the source of malfunctioning of insurance markets.

It is widely argued that adverse selection and moral hazard arise when there is asymmetric information. In insurance markets, (potential) insurance subscribers typically have private information about their riskiness (i.e. hidden types) and about their behaviour (i.e. hidden actions) that insurance companies do not possess. The high-risk type insurance subscribers would seek wider insurance coverage than the low-risk type, i.e. adverse selection (Rothschild and Stiglitz, 1976). Also, insurance subscribers with wider coverage will exert fewer efforts on prevention *ex ante*, increasing riskiness, leading to *ex ante* moral hazard (Arnott and Stiglitz, 1988). In both cases, we should observe a positive correlation between risk and insurance subscription and coverage (Chiappori and Salanié, 2013). The RIETI survey contains information about the subscription status for both property insurance and business interruption (BI) insurance before and after the 2011 floods. Because the data from the RIETI survey does not provide direct information about the *ex ante* prevention efforts by the plants, we focus on the difference in insurance subscription across different locations to test the existence of adverse selection rather than testing *ex ante* moral hazard. The other type of moral hazard, i.e. *ex post* moral hazard, may involve reduced recovery efforts upon receiving insurance payments. The RIETI survey provides us with data that may represent recovery efforts; thus, we test *ex post* moral hazard for both property and business interruption insurance.

[9]'BCP introduced after the 2011 floods' measures if the firm has revised its perception and preparedness for severe adverse events such as floods given its experience.

Upon these observations, we test the following two hypotheses: (i) *Property and/or Business Interruption insurance suffers from adverse selection.* (ii) *Property and/or Business Interruption insurance causes (ex post) moral hazard.* We expect that adverse selection exists for both property and BI insurance, since location choices made prior to the floods would play a key role, and the revelation of potential riskiness of the location leads to missing markets. By contrast, we expect *ex post* moral hazard is more serious for BI insurance, because recovery efforts may not be directly observable by the insurers, i.e. hidden actions from the perspective of insurers. In what follows, we explain how we test the two hypotheses above for both property and BI insurance.

3.1 Adverse Selection

To test the existence of adverse selection, we examine the patterns of insurance subscription before and after the 2011 floods by paying particular attention to plant locations, as well as inundation depth and direct financial losses. First, we directly examine if risk perception about vulnerability against floods and subscription status were different prior to the 2011 floods between different groups of firms. Specifically, we define the following three pairs of groups based on flood damage: (1) Between plants located in Ayutthaya/Pathum Thani and the rest; (2) Between plants that were inundated and the rest; (3) Between plants incurred direct physical losses and the rest. We test if the differences between each pair are statistically significant by comparing the sample means by t-tests.

Risk perception is measured by the reasons for plant location choice. Specifically, respondents were asked to select all applicable reasons from a set of plausible reasons, including 'Because natural disasters occur infrequently'. We assign an indicator variable 'High Risk', which is unity if the plant's answer does not include 'Because natural disasters occur infrequently', and zero otherwise.

Furthermore, using the whole sample, we estimate the following difference-in-difference

(DID) regression model: For every plant i, location d, and period t,

$$Sub_{i,d,t} = \beta_0^S + \beta_1^S AP_d + \beta_2^S T_t + \beta_3^S AP_d \cdot T_t + \beta_4^S Assets_{i,t} + \varepsilon_{i,d,t}^S, \tag{1}$$

where $Sub_{i,d,t}$ is the insurance subscription status dummy at time t, AP_d is the Ayutthaya-Pathum Thani indicator, T_t is the after-2011-floods indicator (i.e., $T_1 = 1$ after the 2011 floods and $T_0 = 0$ before the floods) and $Assets_{i,t}$ is the natural logarithm of total assets of plant i (or the firm's that owns the plant) at time t. The outcome variable $Sub_{i,d,t}$ is an indicator variable, and model (1) is therefore a linear probability model and the regression coefficients may be interpreted as the incremental changes in the subscription likelihood.

The key test for the existence of adverse selection is the sign of β_3^S. Namely, a negative β_3^S indicates that the insurance market may have gone missing for plants located in Ayutthaya and Pathum Thani upon the 2011 floods. This is consistent with the prediction of Rothschild and Stiglitz (1976) in the sense that no (pooling) equilibrium may exist when adverse selection is present – the (re)insurance companies that used to offer insurance opportunities before the 2011 floods have learnt the existence of severe adverse selection issues from the 2011 floods and subsequently withdrew their offers or drastically raised insurance premium to the plants located in Ayutthaya and Pathum Thani. Meanwhile, a positive β_1^S, too, does not contradict with the existence of adverse selection, since it means that plants located in Ayutthaya and Pathum Thani were more likely to have subscribed to insurance than plants located elsewhere. However, this interpretation is subject to a restrictive assumption that there are no systematic differences in unobserved plant characteristics that drive subscription patterns between plants located in Ayutthaya/Pathum Thani and others. Hence, it is a negative β_3^S, rather than a positive β_1^S, that would more directly indicate the existence of adverse selection before the 2011 floods.

Finally, the identification assumption of the DID model (1) is the absence of parallel trends. In our context, the assumption is that before the floods, there are no systematic differences between plants located in Ayutthaya/Pathum Thani and others regarding business performance trends. To check this, we use the year-on-year assessment of the overall performance, sales, and profit in March 2011 and confirmed that there are no such parallel trends. Appendix Table A.2 reports the results.

3.2 Moral Hazard

Turning our attention to moral hazard, we study the impacts of insurance on recovery efforts made by the plants after the floods. To be more specific, plants who had subscribed to insurance (BI insurance in particular) would have weaker incentives to make recovery efforts if insurance payment is paid out quickly.

To measure the impacts, we use an ordered qualitative variable of changes in the production level (ΔY) and that of changes in the number of workers employed (ΔL). Note that there is no quantitative interpretation for the values of these variables. For every plant i, these variables take the following ordered categories since the 2011 floods: $\Delta Y_i \in$ {production has increased; production remains the same; production has decreased; production has been stopped} and $\Delta L_i \in$ {the number has increased since June 2011; the number remains the same since June 2011; the number has decreased since June 2011}.

Since ΔY_i and ΔL_i are both categorical, we estimate the following ordered probit model. For every plant i's $outcome_i$ (i.e. ΔY_i or ΔL_i), we postulate a model for a latent continuous variable, $outcome_i^*$, as follows:

$$outcome_i^* = \beta_0^o + \beta_1^o Paid_i + \beta_2^o Delay_i + \beta_3^o Losses_i + \beta_4^o Assets_{i0} + X_i\gamma + \varepsilon_i^o, \qquad (2)$$

where $Paid_i$ is the insurance payment status indicator ($Paid_i = 1$ if plant i had received an insurance payment by the time of the RIETI survey), $Delay_i$ is the number of months from October 2011 until the insurance payment, $Losses_i$ is the natural logarithm of [monetary value of losses plant i incurred + 1], $Assets_{i0}$ is the pre-floods total assets that would describe the size of the productive capital of plant i (Okubo and Strobl, 2021), X_i is a set of control variables, and ε_i^o is an error term that follows the normal distribution. The control variables include industry fixed effects following Leiter et al. (2009) and the experience of the 1995 floods, which measures 'climate controls' proposed in Elliott et al. (2019).[10] Note that we set $Delay_i = 0$ for plants that did not receive insurance payment, i.e. $Paid_i = 0$. We interpret β_1^o as the effect of insurance payment and β_2^o as the marginal effect of the number of months of delayed payment for plants paid at some time.[11]

It is important to point out a limitation of the specification in equation (2). Because of limited data availability, we are unable to control for 'intangible asset share' used in Leiter et al. (2009). On one hand, intangible asset share is likely to be negatively correlated with property insurance subscription since property insurance covers only tangible assets. On the other hand, intangible assets are held by relatively young and growing firms, so that growth rates of production and employment is likely to be large for those firms. Therefore, the direction of the missing variable bias is negative for property insurance subscription. In contrast, for BI insurance, the correlation between insurance payout and intangible asset share is uncertain, so is the direction of bias. We leave addressing this potential bias for future works.

To further our test of moral hazard, we measure moral hazard by the length of time took until resumption of production. We define time until resumption RT_i as the number of months from October 2011, e.g., $RT_i = 2$ if the firm resumed production in December 2011.[12] We employ two-sided truncated Tobit on the length in months taken for recovery, where non-disrupted plants on the lower truncation and yet-to-recover plants on the upper truncation. We then estimate the following model, separately for property insurance and

[10] While Elliott et al. (2019) provide a detailed set of climate control variables including rainfall and temperature, our dataset lacks these variables. Therefore, we proxy the climatic conditions that may affect the plant's productivity using the past flood experience. Note that our geographical scope is at a regional level, not at the national level; thus, the variations in climatic conditions are limited.

[11] To see this, we rewrite equation (2) as follows:

$$
\begin{aligned}
outcome_i^* &= \beta_0^o + \beta_1^o Paid_i + \beta_2^o Delay_i + \beta_3^o Losses_i + \varepsilon_i \\
&= \beta_0^o + \beta_1^o Paid_i + \beta_2^o Delay_i \cdot Paid_i + \beta_3^o Losses_i + \varepsilon_i^o \\
&= \beta_0^o + Paid_i \cdot (\beta_1^o + \beta_2^o Delay_i) + \beta_3^o Losses_i + \varepsilon_i^o .
\end{aligned}
$$

The second equality follows from the fact that $Delay = 0$ if $Paid = 0$.

[12] There is a categorical answer 'resumed in March-April 2012', which means the firm resumed operation in 5–6 months. To make the linear regression interpretation more straightforward, we treat this answer as 5.5 in the regressions.

for BI insurance:

$$RT_i = \beta_0^R + \beta_1^R Paid_i + \beta_2^R Delay_i + \beta_3^R Losses_i + \varepsilon_i^R. \tag{3}$$

In this regression, the coefficients of interest are β_1^R and β_2^R, which represent the effect on the resuming time of insurance payout and the marginal effect of the number of months of delayed payout, respectively.[13]

4 Estimation Results

In this section, we report the estimation results to examine if the null hypotheses of non-existence of adverse selection and/or moral hazard are rejected. First the results on adverse selection are reported, followed by those on moral hazard.

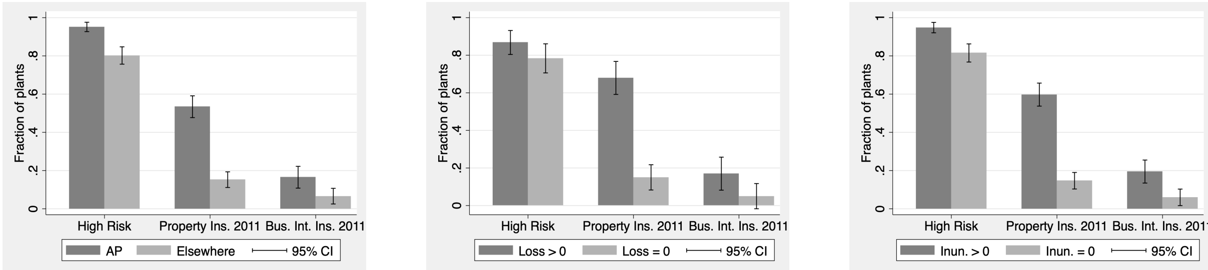
4.1 Adverse Selection

In what follows, we examine if there was an adverse selection problem in the corporate insurance market in our context. Figure 1 compare three different pairs, i.e. by location (Ayutthaya/Pathum Thani versus others), by losses (losses versus no losses), and by inundation (inundated versus no inundation), on the likelihood of 'High risk', defined in Section 3, and on the likelihood of subscribing to property insurance and BI insurance before the 2011 floods (i.e. $Sub_{i,0} = 1$). From panel (a), it is clear that plants in Ayutthaya and Pathum Thani were more likely to be aware of vulnerability against flooding and were also more likely to be subscribing to property insurance before the floods, suggesting adverse selection. Also, from panel (b), plants that incurred losses were also more likely to be aware of vulnerability against flooding, and that, they were also more likely to be subscribing to property insurance before the floods, suggesting adverse selection. Panel (c) tells that the same applies to plants that suffered from inundation, with reduced

[13]Considering possible endogeneity issues arising from pre-floods insurance subscription, we also estimated alternative specifications with an insurance-subscription indicator variable as an additional control to mitigate potential endogeneity bias. Our main results are maintained qualitatively (Appendix A.5).

Figure 1: Adverse Selection: Tests of Mean Differences

(a) By Location (b) By Losses (c) By Inundation



Note: The authors' calculation based on the RIETI survey dataset. Figures compare the fraction of firms that perceived high risk and are covered by property insurance ('Property Ins') and business interruption insurance ('Bus. Int. Ins') in 2011 before the floods. 'High risk' indicates that 'Because natural disasters occur infrequently' is not included as a reason for the plant's location choice. 'Covered 2011' refers to property insurance subscription in 2011 before the floods. The whiskers are the 95 percent confidence intervals. AP stands for Ayutthaya and Pathum Thani provinces. 'Loss > 0' indicates that the firm reported positive financial losses. 'Inun > 0' means that the firm experienced a water positive height on-site during the 2011 floods.

precision because of missing values. Hence, the results reported in panels (a)–(c) suggest the existence of adverse selection in the property insurance market before the 2011 floods.

To further examine the existence of adverse selection, we turn to the analyses that involve comparisons of insurance markets before and after the floods using regression equation (1). Table 2 reports the estimation results.[14] Recall the high subscription rate for firms in Ayutthaya and Pathum Thani provinces before the floods in Figure 1. The results reported in Table 2 are consistent with this finding: The coefficient on AP (Ayutthaya/Pathum Thani indicator) is positive and significant for both property and BI insurance. Moreover, the coefficient on the interaction term of AP and T is negatively significant. Specifically, the subscription rate for property insurance (BI insurance, respectively) decreased by 42 (22, respectively) percent points more in Ayutthaya and Pathum Thani provinces than in other provinces after the 2011 floods. This indicates that the subscription rate in Ayutthaya and Pathum Thani provinces disproportionately decreased after the 2011 floods. This may be reflecting the drastic reduction in insurance supply in Ayutthaya and Pathum Thani provinces: Because of the severe extent of adverse

[14]Our results do not contain flood-unrelated control variables, as they are balanced between flooded locations and non-flooded ones. In fact, inclusion of such variables does not change the result qualitatively. The results are available upon request.

Table 2: Adverse Selection – Regressions of insurance subscription ($Sub_{i,t}$)

VARIABLES	(1) Property	(2) Property	(3) BI	(4) BI
AP	0.590***	0.592***	0.274***	0.274***
	(0.0500)	(0.0539)	(0.0558)	(0.0563)
T	0.0609	0.0457	-0.000	-0.0163
	(0.0523)	(0.0512)	(0.0162)	(0.0171)
$AP \times T$	-0.420***	-0.418***	-0.223***	-0.219***
	(0.0546)	(0.0548)	(0.0262)	(0.0285)
Assets		0.0441***		0.0434***
		(0.0114)		(0.0116)
Constant	0.157***	-0.0975	0.0660***	-0.179***
	(0.0389)	(0.0708)	(0.0188)	(0.0610)
# of Firms	300	300	300	300
Observations	600	600	600	600
R-squared	0.204	0.225	0.096	0.136

Note: The coefficients of model (1) are reported. The top row indicates the outcome variable, the dummy variable for subscribing each type of insurance. 'Bus. Int. Insurance' stands for business-interruption insurance. 'AP' is the Ayutthaya/Pathum Thani indicator variable. 'T' is the after-2011-floods dummy. 'Assets' is natural logarithm of financial assets. Standard errors are clustered by industrial estates in Table A.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

selection revealed after the floods, (re)insurers curtailed insurance supply at a reasonable premium for plants located in Ayutthaya and Pathum Thani provinces, resulting in the lower subscription rate.

To check further that the main results above are indeed driven by adverse selection, we conduct a placebo test by using variables related to labour dispute settlement methods that would measure risk handling intensity, which are not directly affected by the floods. Specifically, a plant may attempt to mitigate the risk of labour disputes by permitting unionization and behaving cooperatively with the union in setting pay and conditions. We measure the leniency of such behaviours and examine how it relates to location (Ayutthaya/Pathum Thani vis-à-vis others) and time (before and after the floods). We find no significant difference in either aspect, corroborating that the floods changed property and BI insurance markets through the revelations of location-related risk information. Further details are reported in Appendix Table A.3.

4.2 Moral Hazard

Next, we examine moral hazard. Table 3 reports the estimation results of model (2). i.e. the impacts of insurance payments on the change in production level and on the change in the number of workers.

From Table 3, it is evident that property insurance subscription has no significant impacts on production and employment level recovery, since the insurance payment status indicator $Paid_i$ is insignificant in all specifications. In contrast, $Paid_i$ is statistically significant for BI insurance on the change in production level and on the change in the number of workers. This suggests that plants who received insurance payments for business interruptions tended to reduce their production level or their number of workers. Meanwhile the timing of insurance payment $Delay_i$ is insignificant in all specifications for property insurance, but is significant in some specifications for BI insurance.[15]

To see further if this dispersion is the result of *ex post* moral hazard caused by insurance payments, we report the estimation results on the length of production suspension based on model (3) in Table 4. $Paid_i$ is now positively significant for both property and BI insurance. Considering the fundamental role of insurance to help companies protect against risks, those who received insurance payments should have resumed their operations earlier than those who were uninsured (i.e., the sign of the coefficient of $Paid$ should be negative), provided that there are no incentives and/or contract enforcement issues. Hence, our finding of the opposing signs of the estimated coefficients is consistent with the existence of *ex post* moral hazard for both property and BI insurance. Furthermore, losses from the floods are positively correlated with the length of suspension. Controlling for the losses therefore makes the coefficient of $Paid$ smaller for both property and BI insurance, although the statistically significant positive effects persist.

Table 4 also reveals that the impacts of the timing of insurance payment ($Delay_i$) are different between property and BI insurance: it is insignificant for property insurance, but is significant for BI insurance. Hence, when the BI insurance payment takes more

[15]In Appendix A.4, we report the results with other outcome variables, the change in the number of engineers and the change in the number of line managers.

Table 3: Moral hazard: Impacts of insurance payment on recovery efforts

VARIABLES	(1) ΔY^P	(2) ΔY^P	(3) ΔY^P	(4) ΔY^P	(5) ΔY^P	(6) ΔY^W	(7) ΔY^W	(8) ΔY^W	(9) ΔY^W	(10) ΔY^W
Property Paid	-0.643	-0.198			-0.0628	-0.308	0.0303			0.338
	(0.512)	(0.610)			(0.659)	(0.646)	(0.825)			(0.787)
Property Delay	0.0244	0.0161			0.00780	0.0142	0.0102			-0.00515
	(0.0410)	(0.0458)			(0.0527)	(0.0481)	(0.0509)			(0.0552)
Bus. Int. Paid			-1.303***	-0.907***	-0.788			-1.980***	-1.725**	-1.885***
			(0.320)	(0.340)	(0.558)			(0.697)	(0.737)	(0.672)
Bus. Int. Delay			0.0812**	0.0642*	0.0459			0.113*	0.103	0.106
			(0.0367)	(0.0375)	(0.0689)			(0.0637)	(0.0648)	(0.0785)
Assets		0.167***		0.164***	0.163**		0.130*		0.129*	0.128
		(0.0620)		(0.0630)	(0.0652)		(0.0750)		(0.0784)	(0.0793)
Losses		-0.180**		-0.167**	-0.177**		-0.0677		-0.0323	-0.0525
		(0.0760)		(0.0662)	(0.0724)		(0.0880)		(0.0849)	(0.0822)
Observations	271	271	271	271	271	242	242	242	242	242
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The average marginal effects of the ordered probit model (2) are reported. For each property insurance (label 'Property') and business-interruption insurance (label 'Bus. Int.'), variable Paid indicates an indicator variable with 1 when the insurance is paid to the firm after floods and 0 otherwise. Variable Delay is the number of months from July 2011 until insurance payment. Variable Assets is natural logarithm of financial asset in 2011. Variable Losses indicates natural logarithm of (monetary value of losses due to the floods +1). Other controls include the flood experience in 1995 and the firm age. Standard errors are clustered by 65 industrial estates. As reported in Table 1, some firms do not report outcome variables, who are dropped from regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Moral Hazard: Regressions of length of suspension (RT_i) on insurance payment

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Resumed Month	Resumed Month	Resumed Month	Resumed Month	Resumed Month
Property Paid	4.009***	2.224***			1.892**
	(1.027)	(0.818)			(0.740)
Property Delay	-0.0590	-0.0212			0.00712
	(0.0839)	(0.0767)			(0.0796)
Bus. Int. Paid			4.316***	2.283*	1.765*
			(1.373)	(1.328)	(1.024)
Bus. Int. Delay			-0.257***	-0.208**	-0.167*
			(0.0906)	(0.101)	(0.0869)
Losses		-0.160		0.0552	-0.181
		(0.105)		(0.0679)	(0.123)

Note: The coefficients of model (3) are reported. For each property insurance (label 'Property') and business-interruption insurance (label 'Bus. Int.'), variable Paid indicates a dummy variable with 1 when the insurance is paid to the firm after floods and 0 otherwise. Variable Delay is the number of months from July 2011 until insurance payment. Variable Damage indicates natural logarithm of (monetary value of losses due to the floods +1). Standard errors are clustered by industrial estates in Table A.1. R-squared is not reported because model (3) is estimated as an ordered probit model. As reported in Table 1, some firms do not report outcome variables, who are dropped from regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

time, plants tend to resume production earlier, or conversely, plants who received quicker insurance payments tend to delay their resumption of production. Since BI insurance payments are usually based on the actual loss of earnings or profits, more prolonged disruptions would increase the payments. It is however not certain *ex ante* if insurance payments for business interruptions will be made, and a quicker payment resolves the uncertainty earlier. These features of BI insurance and our result suggest that a quick BI insurance payment provides the plants with a perverse incentive, offering more breathing space so that they could delay the recovery, i.e. yet another sign of moral hazard.

5 Conclusion

In this paper, we empirically investigate corporate insurance against disasters, which is an area in the existing literature that is under-investigated. In particular, we tested the existence of adverse selection and moral hazard in the corporate insurance market empirically with a unique dataset on the 2011 Thailand floods, which was exclusively collected.

Two empirical results emerge: First, property insurance subscription before the 2011 floods was systematically higher amongst plants located in areas that were directly affected by the floods than amongst others, indicating the existence of adverse selection. Before the 2011 floods plants in the lower Chao Phraya basin, where the floods hit most severely, were more likely to be aware of the flooding risk and to subscribe to property insurance than plants elsewhere did. Furthermore, insurance penetration among plants located in the lower Chao Phraya basin has fallen more than among plants located elsewhere since the 2011 floods, possibly because of the withdrawal of insurance companies from the property insurance market in the lower Chao Phraya basin triggered by the floods, i.e., missing markets.

Second, BI insurance payment is associated with a large decrease in production level and worker employment after the floods, suggesting the existence of moral hazard. While BI insurance is frequently promoted to help smooth the cash flow of the insured when they face disruptions or suspensions of production, the very fact that easier smoothing of cash flow is providing the insured with a perverse incentive to reduce recovery efforts.

Returning to this paper's original observation of the globally low disaster insurance penetration, our findings support the hypothesis that adverse selection would particularly be one of the critical elements that cause the lack of insurance, because it may lead to a complete collapse of the insurance market (Rothschild and Stiglitz, 1976). It would then be natural to ask what drives adverse selection in disaster insurance markets. If the risk aversion motive for insurance subscription holds, then the government's generous *ex post* bail-out policy measures to the affected may well crowd out the demand for private disaster insurance, especially among those with lower disaster risks (Camerer and Kunreuther, 1989). According to descriptive statistics from our data, however, expectations for the government's rescue package do not necessarily cause low-risk plants' absconding from purchasing disaster insurance and high-risk plants are more sensitive to the government's potential post-disaster rescue measures (Appendix A.3, Figures A.5 and A.6). This result is consistent with the argument that the risk aversion motive does not hold for corporate insurance demand. Nevertheless, the exact mechanism that drives the distinctly different behaviours between low-risk and high-risk plants remains unclear. Exploring such a mechanism is an issue that deserves further investigation in the future, although it is beyond the scope of the present paper.

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A Online Appendix

In this section, we provide detailed information about the data including maps, industrial estates/parks (clusters), and engineer and line manager employment. We also report some robustness exercises about our main empirical results.

A.1 Locations and Maps

Figure A.1: Provinces studied

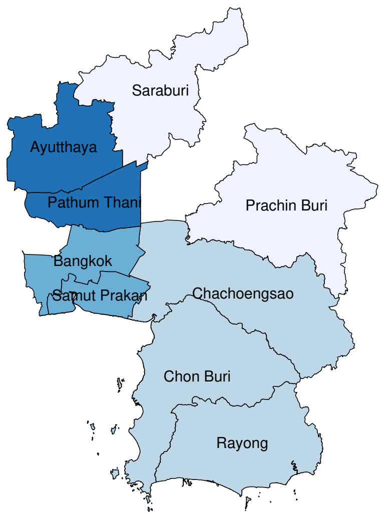


Figure A.2: Sample size for each province

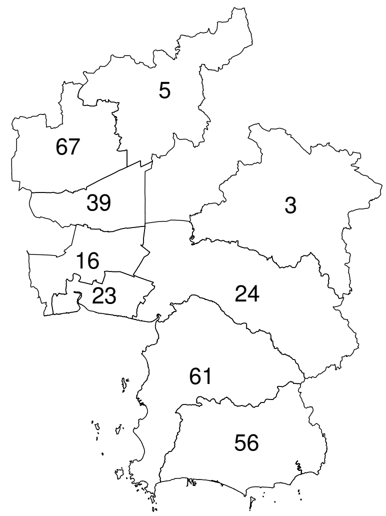


Figure A.3: Max no. of days inundated

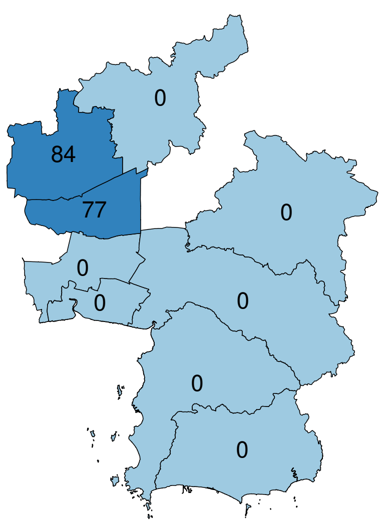


Figure A.4: Max inundation depth (meters)

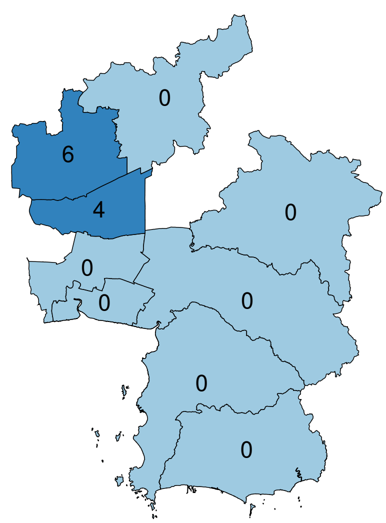


Table A.1: List of Industrial Estates/Parks

Industrial Estates/Parks	Number of Sampled Plants	Share (%)
Saha Rattana Nakorn	2	1
Hi-Tech	23	8
Bangpa-in	10	3
Rojana- Ayutthaya	30	10
Nava Nakorn- Pathumthani	29	10
Bangkadi	8	3
Bangchan	1	0
Lad Krabang	11	4
Bangpoo	10	3
Bangplee	7	2
Gateway City	16	5
Wellgrow	6	2
Amata Nakorn	35	12
Pinthong	11	4
304 IP I	3	1
Laem Chabang	3	1
Eastern Seaboard (Rayong)	29	10
Hemaraj Eastern Seaboard	7	2
Siam Eastern	2	1
Amata City	7	2
Rojana- Rayong	1	0
Hemaraj Rayong Industrial Land	1	0
Rayong Industrial Park	1	0
Asia IE Mapta Phut	5	2
Hemaraj Eastern	1	0
Padaeng	1	0
Hemaraj Saraburi IL	2	1
Others locations	38	13
Total	300	100

Note: The authors' tabulation the RIETI dataset's industrial estate question. "Others" category is the sum of firms that answered other industrial estates or did not answer the question.

A.2 Analysis of Parallel Trends

Table A.2 shows the result of the parallel trend analysis that shows no systematic change in the year-on-year assessments of firm performance, sales, and profit before the floods (in the period of January-June 2011).

Table A.2: Parallel Trend Tests

VARIABLES	(1) Performance	(2) Sales	(3) Profit
AP	-0.0731	-0.111	-0.0338
	(0.126)	(0.242)	(0.172)
Observations	171	300	163
R-squared	0.021	0.144	0.017

Note: The authors' calculation based on the RIETI survey dataset. *AP* is an indicator of location in Ayutthaya and Pathum Thani. Outcome variables are the year-on-year assessment of overall performance, sales, and profits. Due to the survey non-response to the year-on-year assessment variables, the sample size varies across columns. Standard errors are clustered by industrial estates in Table A.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.3 Placebo Analysis

For the placebo analysis described in Section 4, we construct the following two variables. The first variable 'Cooperativeness' is based on the way how bonus payments are determined at each studied plant. Specifically, from a multiple-choice question in the survey, a plant is defined as *amenable* (the value of the cooperativeness variable is unity) if it answers either 'Determined through discussion with workers prior to mediation proceedings' or 'Determined by agreement with the labour side after starting mediation proceedings'. The plant is defined as *hard-line* (the value of the cooperativeness variable is zero) if it answers 'Trial', 'Determined by management', or 'Others'. Since the variable is a snapshot at the time of the survey, we cannot interact it with the time indicator before and after the floods. Nevertheless, we may relate the variable with the location of the plant. The second variable 'Union' is based on the timing of the formation of trade union at the plant. Since the RIETI survey asks the year of the formation of trade union, we construct the union variable indicating the existence of union before and after the floods, and then run the DID regression with respect to location and time. Table A.3 shows the results, and none of these variables are significantly correlated with the location indicator or the interaction terms with location and time, corroborating that the flood risks do not affect our placebo variables of labour risk management.

Table A.3: Placebo Analysis

VARIABLES	(1) Cooperativeness	(2) Union
AP	-0.0806	-0.0230
	(0.0524)	(0.0234)
T		0.0558***
		(0.0163)
$AP \times T$		-0.0170
		(0.0229)
Constant	0.178***	0.0812***
	(0.0412)	(0.0193)
Observations	300	600
R-squared	0.011	0.010

Note: The authors' calculation based on the RIETI survey dataset. 'Cooperativeness' is an indicator of the plant's attitude to its workforce, defined by the way how bonus payments are determined. 'Union' is an indicator of the existence of trade union in each period. The construction of these variables are described in the text in details. AP is an indicator of location in Ayutthaya and Pathum Thani, while T is the time period indicating after the floods. Standard errors are clustered by industrial estates in Table A.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.4 Other Employment: Engineers and Line Managers

Table A.4 shows the summary statistics about employment of engineers (ΔL^E) and line managers (ΔL^M), whose definitions correspond to that of worker employment (ΔL). Table A.5 shows the result of model (2) with the outcome variables of engineer and line manager employment, respectively.

Table A.4: Summary Statistics on Further Firm Performance Variables

	Location	Decreased	Constant	Increased	Total
Engineer	AP	25	39	25	89
(ΔL^E)	Elsewhere	14	65	68	147
	Total	39	104	93	236
Line Manager	AP	22	45	21	88
(ΔL^M)	Elsewhere	12	81	54	147
	Total	34	126	75	235

Note: The author's tabulation from the RIETI-Orbis BvD-merged data. The table shows the distribution of the changes in production (ΔY) and worker employment (ΔL) before and after the floods. AP stands for Ayutthaya and Pathum Thani.

Table A.5: Impacts of insurance payment on further plant performance variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	ΔL^E	ΔL^E	ΔL^E	ΔL^E	ΔL^E	ΔL^M	ΔL^M	ΔL^M	ΔL^M	ΔL^M
Property Paid	-0.469	-0.167			-0.119	-0.0814	0.119			0.113
	(0.311)	(0.394)			(0.459)	(0.384)	(0.442)			(0.504)
Property Delay	0.0304	0.0279			0.0224	-0.00294	0.000649			0.00456
	(0.0209)	(0.0203)			(0.0268)	(0.0244)	(0.0202)			(0.0257)
Bus. Int. Paid			-0.357	-0.100	-0.0495			-0.187	0.0357	-0.000485
			(0.482)	(0.400)	(0.498)			(0.486)	(0.392)	(0.465)
Bus. Int. Delay			0.0404	0.0340	0.0256			-0.0124	-0.0195	-0.0214
			(0.0311)	(0.0277)	(0.0472)			(0.0289)	(0.0228)	(0.0360)
Damage		-0.0851		-0.0621	-0.0776		-0.130*		-0.114	-0.126*
		(0.0631)		(0.0757)	(0.0707)		(0.0760)		(0.0683)	(0.0730)
Observations	236	236	236	236	236	235	235	235	235	235
R-squared	0.024	0.055	0.038	0.062	0.073	0.010	0.054	0.023	0.057	0.061

Note: The authors' calculation based on the RIETI survey dataset. For each property insurance (label 'Property') and business-interruption insurance (label 'Bus. Int.'), variable Paid indicates a dummy variable with 1 when the insurance is paid to the plant after floods and 0 otherwise. Variable Delay is the number of months from July 2011 until insurance payment. Variable Damage indicates natural logarithm of (monetary value of losses due to the floods +1). Standard errors are clustered by industrial estates in Table A.1. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.5 Controlling for Insurance Subscription Status

A potential issue may arise with our estimation strategy to test moral hazard since only plants subscribing to insurance before the 2011 floods are selected. Specifically, if there is a negative correlation between insurance subscription status and recovery efforts, our model would predict a negative relationship between insurance payout status and efforts, which is caused by the selection instead of the payout status per se. To deal with this issue, we estimate equations (2) and (3) by controling for the pre-floods insurance subscription status. By including this additional control variable, the identifying variation comes from the status of the insurance payout and its delay *within* the group of firms that were insured before 2011, which addresses the above selection issue.

Tables A.6 and A.7 show the estimation results. Table A.6 corresponds to equation (2), where moral hazard is measured in terms of production level. As expected, we find negative point estimates for the added control variable, indicating a selection bias, although the standard errors are large and the estimates are not statistically significant in many specifications. Nevertheless, we also find that the effects of insurance payment and its delay remain significant as reported in Table 3. Table A.7 corresponds to equation (3) that takes the length of suspension as the outcome variable. Here, we find positive point estimates for the insurance dummy variable, indicating a negative selection in the sense that firms with insurance subscription are likely to delay resuming their operation. However, again, the signs of coefficients on the event and delay of insurance payout remain the same, indicating that our main qualitative results stay valid.

Table A.6: Moral hazard: Impacts of insurance payment on recovery efforts

VARIABLES	(1) ΔY^P	(2) ΔY^P	(3) ΔY^P	(4) ΔY^P	(5) ΔY^P	(6) ΔY^W	(7) ΔY^W	(8) ΔY^W	(9) ΔY^W	(10) ΔY^W
Property Paid	-0.616	-0.0759			0.0371	0.0496	0.457			0.766
	(0.565)	(0.675)			(0.708)	(0.721)	(0.890)			(0.880)
Property Delay	0.0281	0.0168			0.0107	0.0164	0.0109			-0.00558
	(0.0417)	(0.0464)			(0.0521)	(0.0485)	(0.0510)			(0.0557)
Bus. Int. Paid			-1.344***	-0.907***	-0.822			-1.870***	-1.669**	-1.964***
			(0.348)	(0.340)	(0.585)			(0.710)	(0.736)	(0.736)
Bus. Int. Delay			0.0920***	0.0642*	0.0505			0.118*	0.108*	0.119
			(0.0350)	(0.0375)	(0.0694)			(0.0620)	(0.0635)	(0.0854)
Assets		0.174***		0.164***	0.169***		0.157*		0.142*	0.154*
		(0.0598)		(0.0630)	(0.0623)		(0.0832)		(0.0825)	(0.0861)
Losses		-0.185**		-0.167**	-0.182**		-0.0802		-0.0240	-0.0638
		(0.0817)		(0.0662)	(0.0785)		(0.0869)		(0.0869)	(0.0826)
Insured 2011	-0.0248	-0.198	-0.0122	-0.00905	-0.171	-0.495	-0.669*	-0.184	-0.217	-0.658*
	(0.307)	(0.322)	(0.184)	(0.164)	(0.334)	(0.312)	(0.351)	(0.221)	(0.237)	(0.362)
Observations	271	271	271	271	271	242	242	242	242	242
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The average marginal effects of the ordered probit model (2) are reported. For each property insurance (label 'Property') and business-interruption insurance (label 'Bus. Int.'), variable Paid indicates a dummy variable with 1 when the insurance is paid to the firm after floods and 0 otherwise. Variable Delay is the number of months from July 2011 until insurance payment. Variable Assets is natural logarithm of financial asset in 2011. Variable Losses indicates natural logarithm of (monetary value of losses due to the floods +1). Other controls include the flood experience in 1995 and the firm age. 'Insured 2011' indicates if the firm is covered by insurance in 2011 before the floods. Standard errors are clustered by industrial estates in Table A.1. As reported in Table 1, some firms do not report outcome variables, who are dropped from regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Moral Hazard: Regressions of length of suspension (RT_i) on insurance payment

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Resumed Month	Resumed Month	Resumed Month	Resumed Month	Resumed Month
Property Paid	3.489***	1.880*			1.483
	(1.157)	(1.078)			(1.030)
Property Delay	-0.0813	-0.0330			-0.00294
	(0.0871)	(0.0826)			(0.0836)
Bus. Int. Paid			3.104***	1.608	2.142*
			(1.177)	(1.064)	(1.109)
Bus. Int. Delay			-0.271***	-0.211**	-0.201**
			(0.0867)	(0.0993)	(0.0776)
Losses		-0.144		-0.0787	-0.165
		(0.108)		(0.109)	(0.124)
Insured 2011	0.392	0.571	3.135***	2.916***	0.592
	(0.846)	(0.886)	(0.605)	(0.601)	(0.870)
Constant	-0.382	-2.058***	-1.066	-3.239***	-2.097***
	(0.878)	(0.627)	(1.018)	(0.835)	(0.640)
Observations	236	236	236	236	236

Note: The coefficients of model (3) are reported. For each property insurance (label 'Property') and business-interruption insurance (label 'Bus. Int.'), variable Paid indicates a dummy variable with 1 when the insurance is paid to the firm after floods and 0 otherwise. Variable Delay is the number of months from July 2011 until insurance payment. Variable Damage indicates natural logarithm of (monetary value of losses due to the floods +1). 'Insured 2011' indicates if the firm is covered by insurance in 2011 before the floods. Standard errors are clustered by industrial estates in Table A.1. R-squared is not reported because model (3) is estimated as an ordered probit model. As reported in Table 1, some firms do not report outcome variables, who are dropped from regressions. *** p<0.01, ** p<0.05, * p<0.1.

A.6 Government Crowding Out

There has been a long strand of literature that studies the impacts of public emergency rescue packages on insurance purchasing behaviour in the private property insurance market. Specifically, if the government provides the affected parties with generous bail-out policy measures, their demand for private insurance may be crowded out (Camerer and Kunreuther, 1989), which could be one reason for the observed low insurance penetration. To test this hypothesis, we leverage some questions in the RIETI survey about expectations for emergency rescue packages from the Thai government and knowledge of the government policy. Specifically, each respondent was asked if it expected temporary tax reliefs (Tax question), low-interest-rate loans (Loan question), extensions of repayment schedules (Extension question), and enhanced lump-sum subsidies (Subsidy question). The survey also asks if the respondent knows the National Catastrophe Insurance Fund (NCIF), which was established by the government in reaction to the floods in order to facilitate a quicker and smoother recovery. These are all pieces of information that have relevance to insurance subscription decisions. Namely, if government policies or expectations for government rescue packages crowd out private insurance subscription, private insurance subscription should be *less* associated with higher expectations for government rescue packages or with higher recognition of (or higher expectations for) the government initiatives for anti-flood measures (such as NCIF).

We plot the fraction of plants that answered yes to each of the above questions for the insured and uninsured in Figures A.5 (Property insurance) and A.6 (BI insurance). The results indicate that firms covered by either type of insurance have *higher* expectations for future government rescue packages and are more likely to recognize the existing countermeasures to floods, except for the Extension question, in which there is no significant difference between the two groups. We therefore conclude that the government crowding-out is not detected in our survey.

Figure A.5: Property

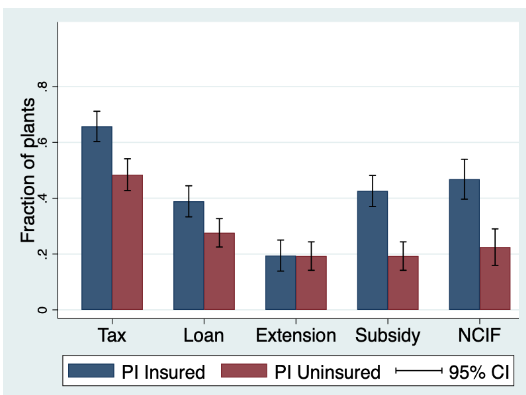
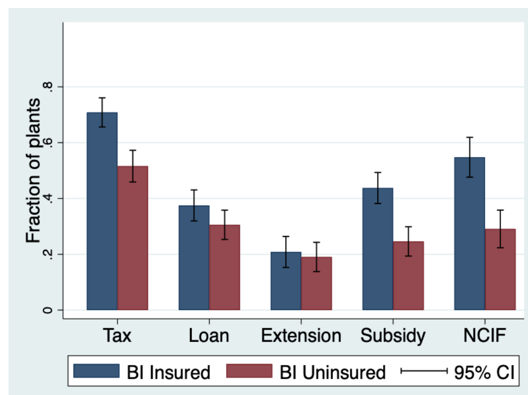


Figure A.6: BI



Note: The fraction of firms that have expectations for the government's rescue packages or recognize the existing measures by the government. 'Tax' asks if the respondent expects temporary tax reliefs, 'Loan' asks if the respondent expects low-interest-rate loans, 'Extension' asks if the respondent expects extensions of repayment schedules, and 'Subsidy' asks if the respondent expects enhanced lump-sum subsidies. 'NCIF' asks if the respondent knows the National Catastrophe Insurance Fund.