Received: 1 December 2020 | Revised: 11 October 2021 | Accepted: 11 October 2021

DOI: 10.1111/jori.12368

ORIGINAL ARTICLE

Journal of Risk and Insurance

Insurability of pandemic risks

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Abstract

This paper analyzes the scope of the private market for pandemic insurance. We develop a framework that explains theoretically how the equilibrium price of pandemic insurance depends on accumulation risk, covariance between pandemic claims and other claims, and covariance between pandemic claims and the stock market performance. Using the natural catastrophe (NatCat) insurance market as a laboratory, we estimate the relationship between the insurance price markup and the tail characteristics of the loss distribution. Then, by using the high-frequency data tracking the economic impact of the COVID-19 pandemic in the United States, we calibrate the loss distribution of a hypothetical insurance contract designed to alleviate the impact of the pandemic on small businesses. The pandemic insurance contract price markup corresponds to the top 20% markup observed in the NatCat insurance market. Then we analyze an intertemporal risk-sharing scheme that can reduce the expected shortfall of the loss distribution by 50%.

KEYWORDS

catastrophe risk transfer, pandemic insurance, private–public partnerships

JEL CLASSIFICATION

G22, G28, G32, J65, H84, Q54

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1 | INTRODUCTION

The economic losses due to the COVID-19 pandemic are estimated at 3.5% contraction of the global gross domestic product (GDP) in 2020 (International Monetary Fund, 2021). Business disruptions have been severe in many sectors of the economy. However, the impact has been particularly devastating for small- and medium-size enterprises in sectors with in-person interactions, such as tourism, transportation, food, recreation, and others. Furthermore, the natural science consensus about the increasing frequency of emerging infectious diseases (Jones et al., 2008; Smith et al., 2014; World Economic Forum, 2019) indicates a growing risk of global pandemics. How can the insurance industry contribute to building resilience to future pandemic events? Is pandemic risk insurable? What is the appropriate allocation of functions between the insurance industry, the financial market, and the government in pandemic risk transfer?

We develop an initial analysis to address these questions by evaluating the price markup, that is, the premium in excess of the expected loss, at which a private insurance market is willing to provide pandemic insurance, theoretically and empirically. We compare the price of a pandemic insurance contract to the equilibrium prices observed in markets for natural catastrophe (NatCat) risks in the United States. Furthermore, we assess the extent to which the pandemic insurance price markup can be reduced by an intertemporal risk-sharing mechanism to remedy the lack of cross-sectional diversification in case of a pandemic. Such a mechanism can be implemented by a long-term intermediary, such as a government. We also discuss some of the challenges and limitations of implementing this mechanism.

The analysis is conducted in the context of a hypothetical insurance contract which is designed to alleviate the economic impact of the pandemic on the revenues and employment of small- and medium-size businesses. The contract provides a monthly compensation during the pandemic, for either the lost revenues of the business or for the lost employment income of its workers. Our choice of a hypothetical contract is motivated by the analyses of Chetty et al. (2020a), as well as Alexander and Karger (2020), that document a sharp reduction in spending within geographic areas with a high COVID-19 infection rate and in sectors with in-person interaction and mobility during the first quarter of 2020. Consequently, these businesses experienced a drastic decrease in their revenues and laid off many workers who are primarily low-wage workers. This channel accounts for the most sizable economic impact of COVID-19 in 2020. Between Q1 2020 and Q2 2020, the US GDP fell by $1.73 trillion. The reduction in consumer spending accounted for $1.35 trillion (an annualized rate of 25%) of the overall GDP reduction.

Pandemic risk is distinct because of a large accumulation risk, under which many contracts are triggered within a short period of time (Hartwig et al., 2020; Richter & Wilson, 2020). We start by providing a theoretical framework that applies the three-moment capital-asset pricing model (CAPM) developed by Kraus and Litzenberger (1976) to characterize the equilibrium of the pandemic insurance market. Including the third central moment of the claim distribution into the analysis allows us to map adequately low-frequency/high-severity situations and formalizes the notion of accumulation risks.

In this setting, we show that the pandemic insurance supply price not only depends on the covariance between a pandemic risk and the traditional CAPM-market portfolio, but also on the covariance between a pandemic risk and all other insured pandemic risks. The resulting risk charge in the insurance premium reflects the cumulative-risk character of pandemic risks that affect many policyholders simultaneously. In addition, the coskewness of pandemic risks with capital markets and insurance risks influences the price for pandemic insurance.

Using the same expected-utility framework that underlies the three-moments CAPM, we derive the maximal willingness to pay for a potential policyholder. We elaborate on the conditions under which a market for pandemic risk is possible, that is, we derive the conditions under which a minimum price of the risk transfer acceptable to an insurer is lower than the maximum willingness to pay for the risk transfer acceptable to a policyholder.

The theoretical framework formalizes that the equilibrium price of insurance depends on the tail behavior characteristics of the loss distribution, the covariance between the pandemic insurance losses and losses of other business lines, and the covariance between the pandemic insurance losses and the stock market returns. We also discuss possible extensions of the model that could lead to an adjustment of the equilibrium markup, that is, extensions regarding insurers' default risk and frictional costs, especially through taxes, bankruptcy risk, and agency problems.

Building on the theoretical framework, we develop an empirical assessment of the equilibrium price markup as a function of the fatness of the tail of the loss distribution and the covariance of insurers' stock returns with the market portfolio using the catastrophe insurance market in the United States as a laboratory. Then we apply the estimated model to evaluate the price of a hypothetical insurance contract.

For practical reasons the empirical pricing model deviates from the theoretical model. Large data samples, which are currently not available, would be needed to provide a stable estimation particularly for the coskewness parameters. Yet, the proposed theoretical pricing model can serve as a benchmark that shows which parts of the potential markup of a competitive insurance premium can already be estimated, and in which direction the empirical markup calculation can be extended in the future, given improved data availability.

Our empirical assessment of the pandemic insurance price markup is conducted in three steps. First, we estimate the relationship between the equilibrium insurance price and the tail characteristics of the loss distribution, relying on extensive data on the NatCat losses, catastrophe insurance premiums, and paid losses in the United States. Second, we calibrate the loss distribution of a hypothetical pandemic insurance contract using the high-frequency granular data on business revenues, business closures, employment, and consumer spending in the United States in 2020. These new and unique data are collected by the Opportunities Insights Team (OIT) and are presented by Chetty et al. (2020b). We link the economic indicators data to the weekly infection rates at the county level obtained from the Center for Disease Control (CDC). By estimating the relationship between the economic indicators and the infection rates, we calibrate the loss distribution of the pandemic insurance contract and its tail characteristics. Third, in the last step, we apply the insurance pricing model for natural catastrophes to evaluate the price markup of a hypothetical pandemic insurance contract and compare it to the actual equilibrium prices of NatCat insurance in the United States.

Clearly, using a pricing model calibrated to the NatCat market has its shortcomings. In particular, the NatCat market does not exhibit the significant accumulation risk of the pandemic event. However, our study offers an initial estimate of the magnitude of the losses of the hypothetical pandemic insurance contract and also provides a starting point for further research on the pricing of such a contract.

Next, we summarize the main parts and findings of the empirical analysis. To estimate the relationship between the markup and the expected shortfall of the loss distribution, we consider a comprehensive sample of the US property–casualty insurers and analyze all business lines with exposure to natural disasters, including auto physical damage, commercial multiple peril, homeowners and farmowners, and special property.[1] The price markup is calculated as the ratio between the direct premiums written (DPW) and the discounted paid losses and other expenses (Cummins & Danzon, 1997; Sommer, 1996). We estimate the natural disasters loss distribution using the highly granular SHELDUS data that report the economic losses and casualties at the county level in the United States.[2] In addition, we obtain the insurers' annual betas by estimating a standard two-factor CAPM for publicly traded insurers (Hartley et al., 2016).

We find that the price markup of NatCat insurance is higher for loss distributions with higher expected shortfall, that is, distributions with higher tail risk, as predicted by the theory. A 10% increase in the expected shortfall translates to a 1.5% increase in the markup. However, the price markup of NatCat insurance is not significantly driven by the covariance between insurers' returns and stock market returns. The latter result reflects the limited impact of the insured NatCat losses for the US economy, even in years with major events like hurricane Katrina in 2005 (Mahalingham et al., 2018).

To assess the loss distribution of the hypothetical pandemic insurance contract, we exploit the OIT data and estimate the relationship between infection rates and changes in small-businesses revenues and employment. We find a strong positive relationship between the reported COVID-19 infection rates and the key indicators of the economic impact, including business revenue reductions, new unemployment claims, and reductions in consumer spending. By using the variation of infection rates across counties in the United States, we calibrate the insurance industry aggregate loss distribution had unemployment lost income been insured. This estimation provides an assessment of the severity of pandemic losses to small businesses and their employees. Thereby, we consider 1-in-100 years frequency as a baseline and extend the analysis to a range of alternative frequencies.

Applying the estimated catastrophe insurance pricing model to the calibrated loss distribution of the hypothetical insurance contract allows us to estimate the price markup for pandemic insurance. Our main result is that the markup of the pandemic insurance contract is substantially higher compared with the markup that insurers charge for insurance with exposure to natural catastrophes. The estimated markup corresponds to the top 20% of the markups charged for catastrophe insurance. The main reason for the elevated price markup is high accumulation risk, that is, high correlation among claims and clustering of claims at the first phase of the occurrence of the pandemic. As a consequence, the pandemic insurance contract losses exhibit a large expected shortfall, which translates into a high insurance price markup.

The empirical analysis suggests that, although there is a scope for the private insurance market for business interruption losses generated by the pandemic, the high accumulation risk of the pandemic insurance contract losses limits the scope for cross-sectional diversification by the insurance industry. As a result, the amount of insurance provided by the private insurance market is limited, and not sufficient to cover the losses comparable to those experienced during the COVID-19 crisis. This causes questions about the scope of the intertemporal risk-transfer

[1]These four categories include the following lines of business with exposure to catastrophe losses: Commercial Auto Physical Damage, Multiple Peril (NonLiability), Earthquake, Farmowners, Federal Flood, Fire, Homeowners, Inland Marine, Multiple Peril Crop, Private Passenger Auto Physical Damage, Private Crop, and Private Flood.

[2]SHELDUS is a county-level hazard data set for the United States and covers natural hazards, such as thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils, such as flash floods, heavy rainfall, and so forth. The database contains crop and damage losses from 1960 to the present.

mechanism facilitated by a long-term intermediary, such as the government, and potentially involving the financial market.

In Section 5 of the paper, we assess the risk-sharing capacity of the intertemporal risk-sharing mechanism that diversifies the pandemic insurance losses across 50 years. Using the calibrated loss distribution of the hypothetical insurance contract, we derive the loss distribution of the risk-sharing scheme. We show that the mechanism enables the reduction of the expected shortfall of the pandemic insurance loss distribution by 50%. However, the expected shortfall remains substantially larger than that observed in the catastrophe insurance market. We also discuss the practical challenges of implementing the intertemporal risk-sharing mechanism that mandates the purchase of reinsurance for all participating insurers, including the entry and exit of insurers from the pandemic insurance market, and the challenges of designing risk-based pricing of reinsurance provided by the scheme.

The paper is organized as follows. Section 2 discusses the factors that limit the insurability of pandemic risks and the application of the three-moment CAPM to explain the pricing of insurance. Section 3 describes the hypothetical insurance contract we use to calibrate the price markup of the pandemic risk. Section 4 contains the empirical analysis to derive the price markup of pandemic insurance. Section 5 evaluates the scope for intertemporal risk-sharing and discusses the challenges of implementation. Section 6 concludes.

2 | FACTORS DRIVING THE INSURABILITY OF PANDEMIC RISKS

2.1 | Overview

The issue of insurability has always been at the core of the insurance literature. A specific risk is defined as insurable by Berliner (1985) and Karten (1997) if the agent exposed to the risk can find a risk carrier who grants the requested cover. Moreover, Berliner (1985) presents a list of criteria of insurability, which has since often been the basis for analyzing insurability, for instance, by Biener and Eling (2012). On the basis of an insurer's strategic objectives, Berliner and Bühlmann (1986) and Nierhaus (1986) set up a framework to analyze the risks for which a (re)insurer would offer coverage. Schmit (1986) clarifies that a decisive requirement of insurability is the predictability of the insurer's loss portfolio. McNichol et al. (2000) argue that the insurability of a particular risk relies on the ability to identify and quantify the risk and the ability to set premiums for each class of customers.

The COVID-19 pandemic has revived the discussion about the insurability of pandemic risk. Though the insurance industry has indemnified the losses that were explicitly insured, for example, trade credit or event cancellation insurance, the COVID-19 crisis has also revealed gaps in insurance coverage that have resulted in claim disputes in business interruption insurance. The key challenges of extending pandemic risk coverage in the future lie in the large loss accumulation risk of pandemic insurance (Hartwig et al., 2020; Klein & Weston, 2020; Richter & Wilson, 2020). Hartwig et al. (2020) and Qiu (2020) also point out that the covariance of pandemic losses with the stock market and with losses in other business lines can further limit insurance capacity.

To cover the insurance protection gap for pandemic risk, particularly for business interruption insurance, Richter and Wilson (2020) suggest that the risk be assumed by the government while the insurance industry provides an administrative support in claims handling. However, Klein and Weston (2020) elaborate on the reasons for the high shadow cost of such a program, particularly due to operational costs, as the implicit promise to bailout private businesses and political interference. Hartwig et al. (2020) and The Geneva Association (2021) analyze the approaches to government involvement to pandemic risk sharing, ranging from postevent financing (like during the COVID-19 crisis), reinsurance, primary insurance, and social insurance funded by taxpayers. They explain the factors driving the operational costs, risk mitigation incentives, funding capacity, and the macroeconomic impact of these programs.

Pandemic risks are low-frequency/high-severity risks. The literature on catastrophe insurance supply (Cummins et al., 2002; Froot, 1999, 2001; Froot & Posner, 2000; Jaffee & Russell, 1997; Niehaus, 2002) provides important insights into the insurability of low-frequency/high-severity risks: Catastrophe risk insurance involves intense risk-sharing within the insurance industry by means of reinsurance and retrocession. Yet, the capacity of the industry is limited by the aggregate size of equity capital. Thus, catastrophe risks can also require risk transfer outside the insurance industry directly to the financial market through securitization (Charpentier, 2008; Cummins & Trainar, 2009; Doherty, 1997).

Due to market imperfections, the private insurance industry set limitations on sharing catastrophe risks, leading to a lack of insurability and implying high insurance premiums and limited equity capital capacity (Winter, 1994). The literature also addresses market imperfections arising from agency problems and capital market frictions (Froot, 2007, 2008; Froot & O'Connell, 2008; Jaffee & Russell, 1997; Zanjani, 2002) as well as ambiguity in assessing catastrophe risks (Charpentier, 2008; Gollier, 1997; Kunreuther & Michel-Kerjan, 2011). As a consequence, the government could play a role as a long-term agent that provides the required loss absorption capacity (Jarzabkowski et al., 2018). However, the analysis of a number of government programs for catastrophe risk financing by Cummins (2006) and Jaffee and Russell (1997) reveals the political pressure, operational inefficiencies, undercapitalization, and market distortions associated with these programs.

Low-frequency/high-severity risks also have implications for insurance demand. Lower take-up rates arise due to the higher elasticity of demand on price, income, and wealth. Grace et al. (2004) document that demand for NatCat insurance is more price elastic than that for non-NatCat insurance demand. Low take-up rates can be driven by budget constraints and charity hazards (Browne & Hoyt, 2000; Grislain-Letrémy, 2018) in which case the latter is a form of moral hazard not to buy insurance in the expectation of a state-provided financial disaster assistance. Other factors that reduce demand for insurance of low-frequency/high-severity events are bounded rationality to assess the impact of these events and distorted incentives for risk mitigation (Kunreuther et al., 2013, 2019).

In addition to NatCat risks, cyber risks and terrorism risks are further examples of low-frequency/high-severity risks. Biener et al. (2015) show that the problems with the insurability of cyber risks lie in the highly interrelated losses, insufficient data availability, and information asymmetries, that is, in moral hazard and adverse selection. Kunreuther and Michel-Kerjan (2004) point out that pricing terrorism insurance needs to account for both systematic and systemic risks.

2.2 | Theoretical example for the demand and supply of pandemic insurance

Recent studies (Hartwig et al., 2020; Klein & Weston, 2020; Richter & Wilson, 2020) identify accumulation risk, covariance between the pandemic losses and the stock market performance, and covariance between the pandemic losses and other insured losses as the key reasons for the lack of insurability. We build a model that explicitly incorporates these features in investors' preferences and policyholder demand to assess their effect on equilibrium insurance prices.

The theoretical framework for the supply side is based on the three-moment CAPM first proposed by Kraus and Litzenberger (1976). Including the third moment accounts for skewed distributions when setting the required return from an investor's perspective.[3] In Appendix A, the derivation of the model is laid out in detail.

In a two-point in time setup with $t = 0, 1$, the insurance premium $P_{0,j}$ of policyholder j for (pandemic) claim payments $S_{1,j}$ is determined by the three factors,

$$P_{0,j} = \frac{1}{1 + r_{\mathrm{f}}}\Big[E(S_{1,j}) - b_1 P_{0,j}\beta_{S_{1,j}} - b_2 P_{0,j}\gamma_{S_{1,j}}\Big], \tag{1}$$

where r_{f} stands for the risk-free rate of return. From the shareholder perspective, the required insurance premium is given by the discounted certainty equivalent that results from adjusting the expected claims payments by two factors. The first factor reflects systematic risk $\beta_{S_{1,j}}$ and has the market risk premium denoted by b_1. The second factor reflects systematic coskewness $\gamma_{S_{1,j}}$, and b_2 stands for the market coskewness premium, which is given by the relation $\mu_{\mathrm{M}} - r_{\mathrm{f}} = b_1 + b_2$, where μ_{M} stands for the expected rate of return of the market portfolio. The definitions of the market portfolio including pandemic losses and the premium loading factors $b_1 P_{0,j}\beta_{S_{1,j}}$ and $b_2 P_{0,j}\gamma_{S_{1,j}}$ are defined and discussed in more detail in Appendix A.

The market price of risk b_1 is positive in a capital market with risk-averse investors and systematic risk. A systematic risk premium charge resulting from a negative systematic risk ($\beta_{S_{1j}}$) comes into play if (a) the (pandemic) loss tends to be above average in times of below-average capital market returns, and if (b) the (pandemic) loss to be insured tends to be above average when the pandemic loss rate is above average, too. The pandemic loss rate is thereby defined by the relation between the aggregate (pandemic) losses and the present value of the market portfolio.

A premium charge resulting from the loading factor $b_2 P_{0,j}\gamma_{S_{1,j}}$ takes place if above-average loss payments prevail in situations of large deviations of the market portfolio return from its mean—which may be due to high pandemic loss rates in otherwise normal capital market scenarios. The more severe the losses are in situations of extreme capital market returns, the higher the markup on the insurance premium becomes. Thus, high cumulative risks, as reflected by a high pandemic loss rate, can exacerbate the coskewness markup through their effect in the market portfolio.

Investors' coskewness preferences imply that the tail characteristics of the loss distribution will affect the equilibrium price of insurance. In particular, the equilibrium price of insurance will be higher for loss distributions with higher accumulation risk, stronger (negative) covariance between the pandemic losses and the stock market, and stronger (positive) covariance between pandemic losses and other insured losses.

Depending on additional assumptions regarding market conditions, the theoretical equilibrium premium can be lower or higher than the one derived in Equation (1). If the default risk

[3]While there has been criticism on the three-moment CAPM by, for example, Post et al. (2008) and Dertwinkel-Kalt and Köster (2019), it is a widely acknowledged pricing approach (see, e.g., Langlois, 2020; Schneider et al., 2020) that seems to be especially suited for pricing insurance for "low frequency–high severity" loss distributions Wen et al. (2008).

of the insurance provider exists, the competitive premium will be lower than $P_{o,j}$. As shown in the seminal paper of Doherty and Garven (1986), the discrepancy between the premium without default risk of the provider, $P_{o,j}$, and the premium with default risk is given by the present value of the default put option. The present value of the default put option results from the discounted expected value E^Q under the risk-neutral distribution Q of the put option $(L_{1,\text{ins}} - A_{1,\text{ins}})^+$. Thereby, $L_{1,\text{ins}}(A_{1,\text{ins}})$ denotes the insurer's stochastic liabilities (assets) at time $t = 1$, and the discount factor is based on the riskless rate of return. As shown in Doherty and Garven (1986), switching from the empirical expectation of the put option $E(L_{1,\text{ins}} - A_{1,\text{ins}})^+$ to $E^Q(L_{1,\text{ins}} - A_{1,\text{ins}})^+$ can be achieved via the risk adjustment of the CAPM. Hence, if the default risk of the provider is of relevance, the introduced model setting can be used, but needs to be adjusted using the present value of the default put option, as laid down in Doherty and Garven (1986), to adjust the insurance premium.[4]

Frictional costs typically increase the premium. In the contribution of Doherty and Garven (1986) and Garven (1992), frictions in the form of corporate taxes are introduced. Assuming that investors are subject to personal taxation and can invest in (risk-adequately priced) assets for which taxation on the corporate level is not in force, the present value of the insurer's corporate taxes is fully added to the competitive premium $P_{o,j}$. Hence, under these assumptions, corporate taxes are solely paid by policyholders. Similar results regarding the pricing of insurance contracts in the context of various agency costs (e.g., costs of equity arise due to the separation of ownership and control) are provided in Braun et al. (2015).[5]

As pointed out in Doherty (1991), Froot and Stein (1998), and Froot (2007), the provider's bankruptcy costs can lead to an additional loading on the premium. In the setting of Froot and Stein (1998), an additional markup on the premium results from (a) the (finite) amount of equity capital of the provider and (b) a convex cost-of-capital function for raising external capital, needed, for instance, to avoid insolvency. Thereby, the provider acts like a risk-averse decision maker requiring a higher insurance premium to avoid or compensate the cost-of-capital surge.[6] However, unlike in the case of an individual decision maker, the degree of risk-aversion is an endogenous variable and results from the influencing factors (a) and (b).

For the demand side, we employ a preference function for the insurance customer that, besides mean and variance of wealth, takes its skewness into account.[7] Purchasing a coverage for insurance is advantageous for a decision maker j if the preference value Φ of her wealth distribution W_1^{with} in $t = 1$ with insurance is larger than the preference value of her wealth distribution $W_1^{\text{w/o}}$ in $t = 1$ without insurance, that is, $\Phi(W_1^{\text{with}}) - \Phi(W_1^{\text{w/o}}) > 0$.[8] By setting $r_f = 0$ and defining the risk adjustment of the insurance contract R_{adj} as presented in Equation (1) by

$$R_{\text{adj}} = -b_1 P_0 \beta_{S_1} - b_2 P_0 \gamma_{S_1}, \tag{2}$$

[4]If the insurer's equity capital is ceteris paribus increased, the present value of the default put option converges to zero. Hence, as Cummins (1988) and Garven (1992) point out, the CAPM can be interpreted as a special case of the option pricing model first presented in Doherty and Garven (1986).
[5]Compare Braun et al. (2015).
[6]In case investors expect an increase of idiosyncratic risk of the insurer through risky asset and liability substitution following pandemic-caused financial distress, such expected “gambling for resurrection” can further increase the required pandemic insurance premium. Risky asset substitution was, for example, documented for life insurance by Wells et al. (2009).
[7]Compare Tsiang (1972), Mitton and Vorkink (2007), and Kraus and Litzenberger (1976).
[8]For simplicity reasons, we omit the index j in what follows.

insurance for pandemic risks will be purchased if

$$-\lambda E[S_1] - (1+\lambda)R_{\text{adj}} + \frac{a}{2}(\text{var}(S_1) - 2\text{cov}(A_1, S_1)) + \frac{a^2}{6}(\gamma_{W_1^{\text{with}}} - \gamma_{W_1^{\text{w/o}}}) > 0. \tag{3}$$

Thereby, A_1 is the insurance customer's stochastic asset endowment at time 1, S_1 is the stochastic (pandemic) loss, λ denotes an adjustment in percent on the premium P_0 (cf. Equation 1) to cover the insurer's default put option value or costs arising from (regulatory) frictions as discussed above, $a > 0$ stands for the customer's risk-aversion parameter and y_{W_1} for the skewness of the customer's wealth distribution.

Inequality (3) provides an economic interpretation of the main factors for purchasing pandemic insurance. By purchasing insurance, the insurance customer gets rid of the risk contribution stemming from the pandemic risk $\frac{a}{2}(\text{var}(S_1) - 2\text{cov}(A_1, S_1))$. The typical case is a negative $\text{cov}(A_1, S_1)$, that is, the loss tends to be above average in states in which the policyholder's assets have a value below average. As an example, a privately owned firm in the tourism sector with different lines of business might be exposed to pandemic-caused business interruption risk in one line of business (e.g., in the hotel sector), and at the same time, noninsurable revenue risks may realize in another line of business (e.g., in renting out apartments). The individual pandemic risk contribution is hereby higher than reflected by the mere loss variance $\text{var}(S_1)$.

The background risk covariance term $\text{cov}(A_1, S_1)$ also maps the phenomenon of "charity hazard," defined by Browne and Hoyt (2000) "as the tendency of an individual at risk not to procure insurance or other risk financing as a result of a reliance on expected charity from others such as friends, family, community, nonprofit organizations, or a government emergency program." A negative $\text{cov}(A_1, S_1)$, before taking unemployment benefits, debt relief, or pandemic-related government aid programs into account, would become smaller in absolute terms by including these measures which raise the value of customer's asset endowment in a pandemic, thus making pandemic insurance purchasing less advantageous.[9]

The last term $\frac{a^2}{6}(\gamma_{W_1^{\text{with}}} - \gamma_{W_1^{(\text{w/o})}})$ in Inequality (3) reflects the individually valued change in the skewness of the customer's cash-flows when purchasing insurance. It can be expected to be positive: Positively skewed uninsured pandemic losses will—due to their negative sign—lower the positive skewness of the insurance customer's wealth position. Therefore, pandemic insurance, by taking away the pandemic risk from the individual, increases the positive skewness of the customer's final wealth, and hence increases her preference value.

The analysis of insurance demand implies that insurance customers are willing to pay a higher price for pandemic insurance if a pandemic risk also affects wealth and income components that are indirectly hit by the pandemic outbreak. An example could be losses in revenues in other uninsured lines of business or higher tax payments in the aftermath of a pandemic to refinance pandemic-related government aid programs. In addition, the insurance customer's willingness to pay increases the more pandemic risks contribute to a lower positive skewness of final wealth if they remained uninsured. If a state-dependent utility function was

[9]The existence of charity hazard in the context of pandemic insurance has been stated in several articles (Hartwig et al., 2020; Klein & Weston, 2020; Richter & Wilson, 2020). As to flood insurance, recent empirical evidence has suggested the existence of charity hazard (Andor et al., 2020; Kousky et al., 2018).

considered,[10] attributing higher disutility to pandemic-induced existence-threatening loss states, an even higher willingness to pay will result.

There are further determinants for the demand of pandemic insurance beyond the proposed theoretical approach: There is experimental evidence that a nonperforming risk of insurance contracts—going either back to an insurer's insolvency or its unwillingness to settle claims—leads to a massive drop in insurance customers' willingness to pay.[11] Insurance demand may therefore decline to an extent that cannot be explained by traditional expected-utility theory. The straightforward reason for nonperforming risk is an increased insurer's underwriting risk through building up a pandemic insurance portfolio. Moreover, since 2020, legal disputes about insurers' obligations to settle pandemic risk losses were observed. Both effects can lead to insurance customers assigning a relatively high nonperforming probability to pandemic insurance coverage resulting in decreased pandemic insurance demand.[12]

(Perceived) nonperforming risk can also increase if insurers suffering huge pandemic losses are expected to "gamble for resurrection" by engaging in risky asset and liability substitution. Given the creditor position of insurance customers, insurance demand will drop due to increasing default risk. Thus, risky asset and liability substitution can be an obstacle for a pandemic insurance market through its impact, both on the insurance price, and the overall risk situation of the insurer.

A comprehensive empirical calibration of the theoretical model setup, as presented and discussed in this chapter, is difficult to obtain. The reasons for that have been widely discussed in the literature (cf. in general Roll, 1977; in particular Cummins, 1991; Cummins & Harrington, 1985), and the arguments raised in these contributions are fully valid until now. In addition, large data samples are needed to provide a stable estimation particularly for the coskewness. This holds particularly true whenever the different variables are not stochastically independent. However, the theoretical model presented in this section is important to clarify which parts of the potential markup on the competitive premium can be estimated yet, and where, in light of the economic benchmark of the theoretical model, the empirical markup calculation can be extended in the future, given improved data availability.

3 | PANDEMIC INSURANCE CONTRACT

We consider a hypothetical contract designed to compensate for the loss of income to individuals employed in sectors that require in-person physical interaction and thereby carry a risk of an infection. In exchange for an up-front premium P, the contract stipulates a contingent constant monthly payment C for T months, triggered by a predefined rule contingent on the infection spread rate, its health impact, and so forth. The probability of the pandemic is q. Then, in the case of a pandemic, the payment of the contract to a policyholder is CT. The expected loss of a contract to an insurer is qCT.

In the baseline calibration, we set $T = 12$ and $C = \$2000$, that is, the contract provides compensation for the loss of basic income of \$2000 for the period of 12 months. We also consider two alternatives, $C = \$1500$ and \$1000. A similar contract can be offered to small

[10] Compare Brown et al. (2016).
[11] Compare Wakker et al. (1997) and Zimmer et al. (2009, 2018).
[12] Compare Samuel (2021) for the respective UK situation.

businesses providing in-person services, in which case the insurance contract would cover the loss of revenue during the pandemic.

The choice of a hypothetical contract is motivated by Chetty et al. (2020a) as well as Alexander and Karger (2020), who argue that the direct financial support to individuals and small businesses is best suited to mitigate the economic hardship during the COVID-19 pandemic. Chetty et al. (2020a) document that high-income individuals sharply reduced their spending in geographic areas with high infection rates and in sectors with in-person interaction. The reduction translated to the decrease in revenue in small businesses that cater to high-income households in person. These services are provided by local businesses, whose revenues in the most affluent zip codes fell by more than 70% between March and late April 2020, compared with 30% in less affluent areas. As businesses lost revenues, they reduced employment, particularly for low-wage employees. These results corroborate the analysis of consumer spending data linked to cell phone records by Alexander and Karger (2020). They find that stay-at-home orders caused large reductions in spending in sectors associated with mobility. Interestingly, Chetty et al. (2020a) also found that state-ordered reopenings of the economies have a small impact on spending and employment, supporting the assertion that the high infection rate collapses the demand for in-person services.

The design of a trigger of a pandemic insurance contract needs to facilitate risk pricing for an insurer. In our empirical assessment below, we rely on the information on infection rates, that is, an objective mechanical trigger. The experience of the COVID-19 outbreak has shown that testing capacity can be limited in the early stages of the outbreak which can delay or reduce the reliability of the objective measures of the infection. An alternative specification of the trigger is a declaration of the epidemic/pandemic by a national or a supranational authority or a shut-down mandated by the government. While such actions might be taken promptly, the trigger based on public authority actions adds political risk and complicates risk pricing. Potentially, a public authority action trigger can also lead to external moral hazard by policymakers, that is, it decreases their incentives to mitigate the consequences of a pandemic outbreak if there is sufficient private insurance coverage (Richter & Wilson, 2020).

4 | EMPIRICAL ASSESSMENT OF THE PRIVATE MARKET FOR PANDEMIC RISKS

We develop an empirical assessment of the market for pandemic risk insurance in the context of a hypothetical insurance contract. The key insight of the theoretical framework above is that the equilibrium insurance price depends on the characteristics of the loss distribution and the interrelationship between the insurers' asset portfolios and prospective policyholders' income loss with the market portfolio. Building on the theoretical framework, in Section 4.2 we start by estimating how the price of NatCat insurance in the United States depends on the tail characteristics of the loss distribution. The estimated pricing model describes the equilibrium pricing of catastrophe risk in a developed insurance market as a function of the tail of the loss distribution characteristics.

Next, we calibrate the loss distribution of the hypothetical insurance contract in Section 4.3. The frequency of the pandemic is calibrated using the epidemiological analysis of the emerging infectious diseases (Jones et al., 2008; Ross et al., 2015). These studies report an increasing frequency of the emerging infectious diseases like COVID-19 driven by socioeconomic, environmental, and ecological factors. Given the high degree of uncertainty and complexity regarding the frequency of these diseases, we use 1-in-100 years as a baseline and calibrate the loss distribution for a range of alternative frequencies. The severity of the losses of the hypothetical pandemic insurance contract is calibrated using the data set on the economic impact of COVID-19 developed by Chetty et al. (2020b) and the Opportunity Insights Team, and the COVID-19 infection rates data.

Using the expected shortfall of the calibrated loss distribution of the hypothetical pandemic insurance contract and the estimated empirical model on the pricing of catastrophe risks, we derive the markup of the pandemic insurance contract. We compare the estimated markup of a pandemic insurance contract to the realized markups in the catastrophe insurance market.

4.1 | Data

Our empirical analysis combines five data sources: information of the economic impact of COVID-19, the US catastrophe insurance market data, the US natural hazard data, and financial market and credit ratings data.

4.1.1 | Data on the economic impact of COVID-19

Chetty et al. (2020b) and the OIT have developed a publicly accessible platform that measures spending, employment, small-business activity, and other economic indicators at a high-frequency granular level using anonymized data from private companies in the United States. Most of the data time series start in 2018 or 2019, depending on the series, and are reported daily at the ZIP code level. Combined with the infection rates reported by the CDC in the United States, the frequency, and the granularity of the OIT data as well as its public access provide a unique opportunity to track the economic impact of the pandemic for individuals and small businesses depending on COVID-19 infection rates and government actions.

4.1.2 | Catastrophe insurance market data

We estimate the model of the equilibrium insurance pricing of NatCat exposures using the insurance company-level data in the United States. In our analysis, we use the annual regulatory statutory filings of these property–casualty insurers to the National Association of Insurance Commissioners (NAIC). The sample consists of the individual insurance companies with DPW in business lines with exposure to NatCat risks as classified by the NAIC in the United States. Twelve business lines are exposed to catastrophe risk, including commercial auto physical damage, commercial multiple peril (nonliability), earthquake, farmowners' multiple peril, federal flood, fire, homeowners' multiple peril, inland marine, multiple peril crop, private passenger auto physical damage, private crop, and private flood. The insurance coverage of these lines includes physical damage to the property from natural hazards or business interruption coverage caused by physical damage, and thus it is subject to catastrophic risks from natural hazards in the hazard-prone zones. We obtain information on the DPW at the state–company–year level. The state-level granularity is important, as states vary in their exposure to natural catastrophes, for example, a hurricane is more likely to occur in Florida than that in Montana.

Although insurers do not report insurance prices in their annual statutory filings, the price markup, that is, the ratio of direct premiums to paid losses for each accident year in a given line of business, can be calculated from the regulatory filings. Consistent with the approach adopted in Cummins and Danzon (1997) and Sommer (1996) to calculate insurance price markups, we collect the information on actual paid losses and other expenses reported in Schedule *P* of insurers' regulatory filings. For each accident year, Schedule *P* provides information on paid losses for the subsequent 10 years for long-tail lines and 2 years for short-tail lines.[13] For long-tail lines, during the 10 years starting from the accident year, the payments related to the losses in the accident year are practically exhausted. Thus, the discounted sum of these payments represents the total paid losses for each accident year. Dividing the DPW by the total paid loss provides a markup, which is a premium above the paid loss for each insured dollar of exposure.

To observe the complete series of loss payments during the 10 years beginning with the accident year, we are restricted by data reporting until 2020 and thus restrict our analysis to the period of 2001–2010. In the case of short-tail lines, the paid losses are reported for the 2 years including the accident year. To compare pricing across short- and long-tail business lines, we collect the data for the same range of accident years 2001–2010 for all lines. Furthermore, the NAIC Schedule *P* reporting standards aggregate the reporting of losses and expenses of the twelve catastrophe risk lines in four broader lines as follows: (1) *auto physical damage*, including commercial auto physical damage and private passenger auto physical damage; (2) c*ommercial multiple peril*; (3) *homeowners' and farmowners' multiple peril*; and (4) *special property,* including earthquake, federal flood, fire, inland marine, and multiple peril crop. Therefore, the analysis of catastrophe risk pricing is conducted for these four business lines.

The initial sample of the US property–casualty insurers consists of 4300 firms. We analyze only those insurers that have positive direct premium written in catastrophe-exposed lines of business in 2001–2010, which reduces the sample to 1118 firms, with a total of 60,167 firm–year–region lines of business observations. The DPW for these lines represent 24% of the total US property–casualty insurance industry premiums in 2010. For the analysis of the effect of market returns on catastrophe insurance pricing, we focus specifically on a sample of publicly traded property–casualty insurers which represent 45% in terms of direct premium written in our sample in 2010. Table B1 in Appendix B reports the list of publicly traded insurance groups included in the sample.

4.1.3 | Data on the frequency and severity of natural catastrophes

SHELDUS is a county-level hazard data set for the United States that covers natural hazards, such as thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils, such as flash floods and heavy rainfall. The database contains information on the date of an event, affected location (county and state), and the direct losses caused by the event (property and crop losses, injuries, and fatalities) from 1960 to the present. Given that we are limited to the yearly granularity of the loss data in Schedule *P*, we aggregate the loss distribution estimates

[13]The long-tail lines with 10 years Schedule *P* reporting of losses and expenses include Homeowner, Farmowner, and Commercial Multiple Peril. The short-tail lines with 2 years' Schedule *P* reporting include Auto Physical Damage and Special Property.

(property and crop losses) to yearly frequency, inflation-adjusted to 2010 as the base year, to the state–year level for the period of 1980–2019.[14]

We model the loss distribution of natural catastrophes on the regional level, in which we follow the S&P Market Intelligence regional classification.[15] These regions contain states with a similar type of natural hazard exposures. The assessment of the loss distribution at the regional level enables us to increase the number of loss events and improves the assessment of the natural hazard loss distribution. We then fit the loss data to a log-normal distribution for each of the six regions: Mid-Atlantic Midwest, Northeast, Southeast, Southwest, and West. The loss distribution parameters are reported in Table 1. Using the fitted loss distributions, we calculate the standard deviation of losses and the 1% expected shortfall of the loss distribution at the regional level.

4.1.4 | Market data

We collect the market data on the S&P 500 index and US 10-year constant maturity note rates for the period 2001–2010 from Bloomberg. For a subset of publicly traded insurers, we also obtain the stock price data for the period of 2001–2010 from Bloomberg, adjusting for corporate actions.[16] To discount the sequence of paid losses obtained from Schedule *P* of the US regulatory filings, we use the US Treasury yield curve.

We obtain A. M. Best insurers' financial strength ratings during 2001–2010. A. M. Best's rating scale includes 14 rating categories ranging from A++ to D, out of which the six top ratings A++ to A− are classified as secure ratings and the bottom eight B++ to D are classified as vulnerable ratings. We aggregate the eight vulnerable ratings into one group as they apply to a small subset (115 out of 1118 insurers) in our data set. The encoding of rating in our data set is from 1—highest to 7—lowest.

4.2 | Pricing tail risk in the NatCat insurance market

4.2.1 | Econometric specification

We use the NatCat insurance market as a laboratory to evaluate how tail factors affect insurance pricing. The three-moment CAPM model discussed above formulates that the equilibrium insurance price depends on the coskewness term containing three tail components: clustering of pandemic claims, covariance of pandemic losses and stock market returns, and coskewness of pandemic losses and other losses.

[14] We tested and found no time trend in the data.

[15] S&P Market Intelligence platform regional classification includes six regions: *Mid-Atlantic* (MA): Pennsylvania, Delaware, New York, District of Columbia, New Jersey, Maryland, Puerto Rico; *Mid-West* (MW): Wisconsin, Illinois, Ohio, Michigan, Iowa, Nebraska, Missouri, Kentucky, Kansas, Minnesota, North Dakota, Indiana, South Dakota; *Northeast* (NE): Massachusetts, Vermont, Maine, Connecticut, Rhode Island, New Hampshire; *Southeast* (SE): Florida, Georgia, South Carolina, North Carolina, Tennessee, Arkansas, Alabama, West Virginia, Mississippi, Virginia, Virgin Islands; *Southwest* (SW): Utah, Texas, Colorado, Louisiana, New Mexico, Oklahoma; *West* (WE): California, Nevada, Wyoming, Arizona, Montana, Alaska, Washington, Hawaii, Idaho, Oregon.

[16] Dividend payments, stock splits, and so forth.

TABLE 1 Natural hazards loss distribution estimates by region

Panel A: Parameters of the fitted log-normal, Gamma, and Weibull distributions as well as the corresponding goodness of fit *p* value. Results show that the null hypothesis of losses being distributed according to log-normal, Gamma, or Weibull distribution, respectively, cannot be rejected for any of the regions at 5%, only for the log-normal distribution

Region	LN parameters		KS test	Gamma parameters		KS test	Weibull parameters		KS test
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MA	19.989	1.301	0.709	0.513	3.21E+09	0.042	0.581	6.17E+08	0.006
MW	21.559	0.833	0.69	1.476	2.28E+09	0.408	1.070	3.06E+09	0.331
NE	18.013	1.405	0.643	0.539	3.95E+08	0.039	0.630	1.19E+08	0.133
SE	21.586	1.334	0.857	0.674	8.67E+09	0.556	0.724	4.07E+09	0.647
SW	21.622	1.232	0.932	0.611	1.10E+10	0.057	0.642	3.22E+09	0.078
WE	20.959	1.419	0.836	0.624	5.44E+09	0.229	0.698	2.34E+09	0.488

Panel B: Columns (2) and (3) report the parameters of the LN distributions. Columns (4)–(6) report the mean, standard deviation, and the 1% expected shortfall, in billion US dollars, respectively

Region	LN parameters		Mean	SD	$ES_{1\%}$
(1)	(2) μ	(3) σ	(4)	(5)	(6)
MA	19.989	1.301	1.1178	2.3435	17.0266
MW	21.559	0.833	3.2625	3.2175	22.0573
NE	18.013	1.405	0.1785	0.4430	3.1835
SE	21.586	1.334	5.7657	12.6677	92.3049
SW	21.622	1.232	5.2473	9.9354	71.6728
WE	20.959	1.419	3.4670	8.8339	63.0065

Note: The table presents the statistics of the distributions fitted using SHELDUS Natural Hazard losses in 1980–2019 data by region. Regions are abbreviated as follows: MA, Mid-Atlantic; MW, Midwest; NE, New England; SE, Southeast; SW, Southwest; WE, West.

We estimate the following regression:

$$\ln(1+\lambda)_{it} = \beta_{\mathrm{vol}}\ln(\sigma^2_{\mathrm{vol}})_{it} + \beta_{\mathrm{ES}}\ln(\sigma^2_{\mathrm{ES}})_{it} + \beta_{\mathrm{R}}\ln R_{it} + \gamma_i + \theta_t + \varepsilon. \tag{4}$$

The dependent variable $(1+\lambda)_{it}$ is the insurance price markup of insurer i in year t, that is, the ratio of DPW in the catastrophe-exposed lines of business to the discounted sum of paid losses (see Section 4.1.2). The first two explanatory variables in (4) are the volatility of the loss distribution $(\sigma^2_{\mathrm{vol}})_{it}$ and the 1% expected shortfall of the loss distribution $(\sigma^2_{\mathrm{ES}})_{it}$ of firm i in year t. R_{it} is the insurers' rating, γ_i and θ_t are the insurer- and year-fixed effects, and ε is the error term to account for the unobserved factors driving the price markup. β_{vol}, β_{ES}, and β_{R} are parameters to be estimated. Next, we explain and motivate the explanatory variables of the pricing model.

The first two explanatory variables in (4), $(\sigma^2_{\mathrm{vol}})_{it}$ and $(\sigma^2_{\mathrm{ES}})_{it}$ are the loss distribution tail statistics that measure the clustering of catastrophe claims. With respect to the three-moment-CAPM pricing formula (see Equation A7 in Appendix A), these two explanatory variables refer to the markup going back to the cumulative-risk character of pandemic risks, and the coskewness markup that is driven by the tail of the loss distribution. We expect that the loss distributions with fatter tails result in higher equilibrium prices of insurance. Therefore, the coefficients to be estimated, β_{vol} and β_{ES}, are predicted to be positive.

In the empirical specification (4), measures $(\sigma^2_{\text{vol}})_{it}$ and $(\sigma^2_{\text{ES}})_{it}$ correspond to the loss distribution of an insurer's NatCat exposure across the geographic regions in which an insurer is active in catastrophe risk business lines. At the same time, Schedule *P* data report the firm-level loss development at the business line and state levels. To construct the firm-year loss distribution at the regional level, we weight the loss distribution in region *j* by α_{itj}, which is the share of DPW in catastrophic risks insurance in region *j* for each insurer–year *it*; that is,

$$\alpha_{ijt} = \frac{DPW_{ijt}}{\sum_k DPW_{ikt}}.$$

To the extent that shares α_{ijt} vary across firms and years, an insurer faces a distinct distribution of losses depending on the profile of its exposures which would lead to distinct values of $(\sigma^2_{\text{vol}})_{it}$ and $(\sigma^2_{\text{ES}})_{it}$ for insurer *i* in year *t*.

Estimation of the impact of the systematic risk of pandemic losses, that is, the covariance between insurers' losses and stock market returns (see Equation A7 in Appendix A), on the price markup requires high-frequency data on insurance claims which are only reported at annual frequency. To overcome this data constraint, we proxy the insurer claim experience by its stock returns which is possible only for a subset of publicly traded insurers. Presumably, high individual insurance company losses translate into negative returns (Ben Ammar, 2020; Thomann, 2013). High losses going along with negative capital market returns contribute to a positive covariance between losses and the capital market. For publicly traded insurers, we estimate a modification of model (4) that also includes the beta of insurers' returns with the market portfolio b_{it} for insurer *i* in year *t*:

$$\ln(1+\lambda)_{it} = \beta_{\text{vol}} \ln(\sigma^2_{\text{vol}})_{it} + \beta_{\text{ES}} \ln(\sigma^2_{\text{ES}})_{it} + \beta_{\text{M}} \ln(1+b_{it}) + \beta_{\text{R}} \ln R_{it} + \gamma_i + \theta_t + \varepsilon, \tag{5}$$

where β_{M} is an additional coefficient to be estimated. We predict that a higher correlation between the insured NatCat losses and stock market results in higher markups, that is, β_{M} is positive.

For a subsample of publicly traded insurers, the comovement between insurer *i's* stock performance in year *t* and the market portfolio in year *t*, b_{it} is estimated using insurers' stock returns and the S&P 500 index in 2001–2010. We employ a standard two-factor CAPM specification following the methodology in Hartley et al. (2016) and estimate the following regression:

$$R_{it} = a + b_{it} R_{\text{m},t} + c_{it} R_{10,t} + \eta_{it}, \tag{6}$$

where R_{it} is the return on stock *i* in week *t*, $R_{\text{m},t}$ is the return on a value-weighted stock market portfolio in week *t*, $R_{10,t}$ is the return on the US government bond with a 10-year constant maturity in week *t*, and η_{it} is a mean zero error term. The insurer–year estimate b_{it} is used as an input in the estimation of the markup regression (5).

The third component of the coskewness term of the three-moment-CAPM model predicts a premium markup due to a positive covariance between pandemic losses and other losses. A limitation of the NatCat insurance market is that there is no covariance between the natural hazard losses and other losses, for example, general liability insurance.[17] Therefore, we cannot include this factor in the pricing model. However, we recognize that this factor can be relevant for pandemics during which pandemic losses are likely to be correlated with losses in other lines like trade credit insurance or event cancellation insurance (Qiu, 2020). In this respect, our analysis of pandemic insurance markup should be interpreted as a lower bound that does not account for the correlation of losses across lines.

Beyond the components of the three-moment-CAPM model, the regression specifications (4) and (5) control for the insurer's financial strength rating R_{it} assigned by the rating agency A. M. Best, and they measure the claims' paying ability of insurers. Inclusion of the rating accounts for the role of the insurer's financial strength for pricing. Policyholders require a discount for insurance with a risk of contract nonperformance (Cummins & Danzon, 1997; Doherty & Schlesinger, 1991; Epermanis & Harrington, 2006; Zimmer et al., 2018). Therefore, the markup decreases in the insurer's rating. Although the insurer's insolvency risk is irrelevant in the three-moment-CAPM analysis, accounting for market imperfections is important in the empirical specification, as demonstrated in our results below.

The summary statistics of the variables in regressions (4) and (5) are presented in Table 2. Table 2 Panel A reports the summary statistics of the markup, volatility, expected shortfall, and a rating in the sample. Table 2 Panel B contains the correlation matrix between the variance, expected shortfall, and the rating. It reveals that there is a strong correlation between the variance and expected shortfall measures. One reason is that our construction of the insurers' catastrophe loss exposures relies on regional loss distributions, which reduces the variability within the regions. As a remedy to the collinearity issue, we estimate the markup model using only the expected shortfall (and not the standard deviation) to characterize the tail of the loss distribution. Table 2 Panel C reports the summary statistics by line of business.

4.2.2 | Empirical results

The estimation results of the markup regressions (4) are presented in Table 3. In Panel A, we report the results of the regression in which all four business lines, auto physical damage, commercial multiple peril, homeowners' and farmowners' multiple peril, and special property, are pooled. The main coefficient of interest measuring the sensitivity of the price markup to the expected shortfall of the loss distribution, is positive and significant. This indicates that a 10% increase in expected shortfall leads to 1.5% increase in the markup. The coefficient measuring the sensitivity of the price markup to the insurer rating is positive but not significant. The regression in Table 3 Panel A also includes (unreported) firm- and year-fixed effects. The insurer-fixed effects are mostly significant. The year-fixed effects are positive and significant for 2008, which coincides with the global financial crisis. Overall, the estimation of the markup regression confirms that insurers charge higher prices for insuring the exposures with higher expected shortfall, that is, higher tail risk.

[17]In unreported analysis available from the authors, we have estimated the covariance between the insurer's NatCat lines losses and losses on other lines and included it as a factor in the pricing model (4). However, the estimation results show that this factor is not significant for the price markup of the NatCat insurance.

TABLE 2 Natural catastrophe market summary statistics

Panel A: Sample statistics for all lines of business						
	(1) Sample size	**(2) Mean**	**(3) Median**	**(4) SD**	**(5) Min**	**(6) Max**
Markup	60,167	3.427	1.731	4.323	0.01	22.273
$ES_{1\%}$ of loss dist	60,167	0.0945	0.0099	0.4510	0.0000	16.5500
SD of floss dist	60,167	0.0131	0.0014	0.0625	0.0000	2.2710
Rating	60,167	2.971	3	1.217	1	7

Panel B: Correlation matrix			
Variables	**(1)**	**(2)**	**(3)**
(1) $ES_{1\%}$	1.000		
(2) SD	0.9999	1.000	
(3) Rating	−0.1005	−0.1008	1.000

Panel C: Summary statistics by line of business					
Line of business		**(1) Auto physical damage**	**(2) Commercial MP**	**(3) Homeowner/ farmowner**	**(4) Special property**
Sample size		20,938	11,214	9527	18,488
Markup	Mean	3.389	2.813	3.303	3.908
	Median	1.691	1.335	1.703	2.107
	SD	4.32	3.929	4.141	4.585
	Min	0.01	0.01	0.01	0.01
	Max	22.266	22.216	22.212	22.273
ES at 1%	Mean	0.0073	0.1230	0.1354	0.0823
	Median	0.0065	0.0217	0.0153	0.0083
	SD	0.5126	0.3454	0.6298	0.2932
	Min	0.0000	0.0000	0.0000	0.0000
	Max	16.5500	4.8700	12.5900	6.9560
Rating	Mean	3.008	2.979	2.951	2.936
	Median	3	3	3	3
	SD	1.269	1.147	1.254	1.177
	Min	1	1	1	1
	Max	7	7	7	7

Note: Panel A of this table presents summary statistics of the variables in the markup regression (4). Panel B reports the correlation matrix of the loss distribution characteristics, expected shortfall and standard deviation, and insurers' ratings. Panel C reports the summary statistics of the variables that enter the markup regression (4) by line of business. Expected Shortfall and Standard Deviation statistics in Panels A and C are reported in billions of US dollars.

TABLE 3 Pricing of natural catastrophe insurance

Panel A: Estimates for the pooled regression

	Ln (markup)
Ln ($ES_{1\%}$)	0.1451***
	(0.0022)
Ln (rating)	0.0385
	(0.0272)
Constant	−2.1198***
	(0.1495)
R^2	0.41
N	60,167

Panel B: Estimates by line of business

Ln (Markup)	**(1)**	**(2)**	**(3)**	**(4)**
Ln ($ES_{1\%}$)	0.0904***	0.0853***	0.0834***	0.1612***
	(0.0030)	(0.0059)	(0.0050)	(0.0047)
Ln (rating)	0.0535*	0.1312**	−0.0461	0.1041**
	(0.0309)	(0.0648)	(0.0511)	(0.0482)
Constant	−0.7095***	−2.3710***	−1.2469***	−2.7699***
	(0.1448)	(0.3119)	(0.2578)	(0.2889)
R^2	0.68	0.55	0.70	0.51
N	20,938	11,214	9527	18,488

Panel C: Test of differences on regression coefficients among the four lines of business

(1) Base	**(2) Compared**	**(3) Ln ($ES_{1\%}$)**	**(4) Ln (rating)**	**(5) Constant**
Line 1		0.1108***	−0.0101	−1.4114***
	Line 2	0.0558***	0.0489	−1.364***
	Line 3	0.0309***	−0.0115	−0.5541***
	Line 4	0.1175***	0.1353***	−1.9233***
Line 2		0.1666***	0.0388	−2.7754***
	Line 3	−0.0249***	−0.0604*	0.8098***
	Line 4	0.0617***	0.0864***	−0.5593***
Line 3		0.1417***	−0.0216	−1.9656***
	Line 4	0.0867***	0.1468***	−1.3691***

Note: Panel A reports the results of the pooled regression (4). Panel B reports regression results by line of business. Panel C provides the pairwise t test for differences between estimated regression coefficients across business lines reported in Panel B. Firm and year fixed effects are not reported for brevity. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

(1) Auto physical damage; (2) commercial MP; (3) homeowner/farmowner; (4) special property.

Due to computational capacities limitations the tests were performed not accounting for differences in firm fixed effects among each pair therefore estimated coefficients differ slightly from those in Panel B. In each subsection, the first row shows the estimated coefficients of the business line-specific regression; the subsequent rows show the difference between the coefficients of the corresponding line with the baseline. The line coding is as in Panel B.

The four catastrophe risk business lines have distinct characteristics in terms of coverage and customers. In particular, the homeowners' and farmowners' business lines are personal insurance lines, while the other lines are either a mix of personal and commercial (auto physical damage) or purely commercial lines (commercial multiple peril, special property). In addition, the special property line is focused exclusively on tail risks related to floods, earthquakes, and other hazards. Furthermore, the special property line is subject to less price regulation, giving more scope for insurers to increase insurance rates for heavy-tailed risks. For these reasons, the price markups can differ across business lines. Therefore, we perform the price markup estimation (4) separately for the four business lines.

The results of the estimation are reported in Table 3 Panel B. Table 3 Panel C provides a formal pairwise test of the differences of the regression coefficients among the four lines of business. The results reported in Panel B confirm that, while the expected shortfall is a significant factor in the price markup in all business lines, there is variation in the pricing factors across lines. The expected shortfall pricing premium is particularly large for the special property lines that primarily cover tail risks. At the same time, the impact of the expected shortfall on the price is less pronounced for homeowners' and farmowners' insurance.

The impact of ratings on pricing also varies across business lines. Ratings matter for the pricing of commercial lines, commercial multiple peril, and special property. However, an insurer rating is only marginally significant (at 10%) for the auto physical damage line, which is a mix of commercial and personal lines. Furthermore, ratings are not significant for the personal lines of homeowners' and farmowners' insurance. These results indicate the varying sensitivity of insurance demand to insurers' insolvency risk between commercial and personal insurance buyers, consistent with Basten et al. (2021) and Epermanis and Harrington (2006), among others.

Next, we evaluate how the NatCat insurance price markup depends on the covariance between the insurers' stock returns and the stock market. Table 4 Panel A presents the estimated market betas of the two-factor CAPM model (6) for the subsample of publicly traded insurers. In the overall sample, the mean and the median betas in Table 4 panel A are 0.799 and 0.813, respectively; the standard deviation is 0.524. In the time series, the betas of the property–casualty companies are increasing over the period of 2001–2010, suggesting that the property–casualty insurance stocks become more synchronized with the market over time, which also reflects the influence of the 2008 financial crisis on the insurers' performance. This trend is robust when the analysis is restricted to those companies present in all years. The interest rates factor in regression (6) is not significant, consistent with the short-term nature of nonlife insurance liabilities.

We estimate the markup regression (5) for a subsample of publicly traded insurers, using the estimation results of the two-factor CAPM. The results are presented in Table 4 Panel B. The coefficient of the market beta is negative but not significant. Hence, the covariance between the insurers' returns and the market does not have a significant impact on the price markup of NatCat risks. This result is consistent with the limited impact of the NatCat events on the financial market. However, the relationship might look different after writing the pandemic insurance. As suggested by the market downturn at the inception of COVID-19 pandemic, one may expect a significant covariance between insurers' losses from pandemic insurance losses and the stock market returns.

TABLE 4 Pricing of natural catastrophe risks for public insurers

Panel A: Estimated market betas of public insurers						
(1) Time period	**(2) Sample size**	**(3) Mean**	**(4) Median**	**(5) SD**	**(6) Min**	**(7) Max**
Overall sample	**440**	**0.799**	**0.813**	**0.524**	**−1.457**	**3.438**
2000	35	0.494	0.472	0.377	−0.434	1.171
2001	36	0.572	0.602	0.312	−0.232	1.542
2002	36	0.594	0.708	0.515	−1.457	1.357
2003	39	0.670	0.775	0.458	−0.195	1.506
2004	42	0.724	0.780	0.427	−0.710	1.570
2005	42	0.672	0.793	0.509	−0.344	1.588
2006	42	0.848	0.855	0.466	−0.716	2.312
2007	42	0.835	0.906	0.402	−0.233	1.640
2008	42	1.000	0.999	0.502	0.008	2.281
2009	42	1.280	1.246	0.702	0.016	3.438
2010	42	0.980	0.989	0.434	−0.111	1.801

Panel B: Markup estimation for public insurers	
	Ln (markup)
Ln ($ES_{1\%}$)	0.1554***
	(0.0032)
Ln (rating)	−0.0048
	(0.0377)
Ln (beta)	−0.0505
	(0.0465)
Constant	−1.8555***
	(0.2072)
R^2	0.42
N	28,282

Note: This table presents summary statistics of the estimated market betas for insurers in our sample. The overall sample includes 42 P&C Insurers for the time period 2000–2010. As not all insurers were publicly traded for the entire period, the number of estimations in each year differs and is presented in column (2). For each insurer–year, the market beta is estimated only if the stock was traded for a minimum of 200 days.

This table presents the estimates of the pricing regression (5). Firm and year fixed effects are not reported for brevity. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

4.3 | Calibration of the pandemic insurance contract loss distribution and its markup

4.3.1 | Calibration of the pandemic insurance contract loss distribution

The insurance payment of the hypothetical insurance contract is triggered by an increasing infection rate which leads to the reduction of in-person business activity due to the risk of infection. To calibrate the loss distribution of the contract, we need to assess the severity of losses and the frequency of pandemics.

Literature on assessing the economic effect of a pandemic typically uses scenario analyses to predict the impact of a global pandemic on economic indicators (Keogh-Brown et al., 2008; McKibbin & Sidorenko, 2006). We employ a different approach by making use of the data reported in Chetty et al. (2020b) and the OIT to calibrate the severity of the pandemic loss distribution in terms of unemployment cost. Table 5 reports the estimates of the changes in different types of economic activity, depending on the newly reported cases of COVID-19 infection. The estimation results indicate a strong statistically and economically significant relationship between the infection rates and the economic activity and employment. Panel A reports the results for the whole period of the COVID-19 pandemic until October 31, 2020. Columns (1) and (2) reveal that the growth in infection rates leads to a rise of new unemployment claims and reduces the employment of workers in the bottom quantile of the income distribution. To illustrate the economic significance, the rise in infection rates from 0.0654 to 49.2 per 100,000 inhabitants, thereby reflecting the dynamics of new cases in New York state during the first COVID-19 wave between 07 March 2020 and 11 April 2020, leads to 1,200,066 new unemployment claims and reduces the employment in the bottom quantile by 6.92%. Column (3) shows that the impact of rising infection rates was also negative for the two middle quantiles of the income distribution, though its magnitude was smaller than for the bottom quantile. The growth of the infection rate also reduces the revenues of small businesses and the number of open small businesses, as reported in columns (4) and (5).

In 2020, the strongest contraction of employment and small-business economic activity occurred during the first wave of the infection in February–March 2020 in the United States. Table 5 Panels B–D report the regression results on the impact of new COVID-19 cases on the initial unemployment insurance claims, the change in the number of small businesses open, and the changes in their revenue, respectively, during the three quarters in 2020. Comparing the regression coefficients between the first and the other three quarters emphasizes the importance of the initial shock of the infection outbreak. Once the businesses are closed and workers are let go during the first quarter, the subdued economic activity persists through the following quarters.

The estimation results of Table 5 allow us to model the loss distribution of the hypothetical pandemic insurance contract. To calibrate the severity of the loss distribution, we use the predicted new unemployment claims occurring due to the growing infection rates as reported in Table 5 at the county level. We consider each county in the United States as a homogeneous unit, and fit the distribution of the predicted number of unemployment claims per county, scaled by a factor equal to US population in 2019 divided by county population in 2019, to a log-normal distribution. In total, our sample consists of 3141 counties in the United States. The result is the empirical distribution of predicted new unemployment claims across the US counties caused by the pandemic. We use this empirical distribution to assess the standard deviation and the expected shortfall of the loss distribution for the hypothetical insurance contract.

Turning to the frequency of pandemics, Jones et al. (2008) report a growing frequency of emerging infectious diseases that, like, COVID-19, originate in wildlife and have recently entered human populations for the first time. The most prominent examples before 2019 were Ebola, HIV/AIDS, and SARS. Ross et al. (2015) discuss the challenges of the international health regulations that need to be resolved to reduce the human and economic damage of emerging diseases. Considering the evolving nature of the risk, we calibrate the model for a

TABLE 5 Economic indicators dependency on COVID-19 new cases rate per 100,000 people

Panel A: Impact of COVID-19 new case on main economic indicators for the time period of 01.02.2020–31.10.2020

	(1)	(2)	(3)	(4)	(5)
COVID-19 new case rate daily		−0.0031***	−0.0012***	−0.0030***	−0.0028***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
COVID-19 new case rate weekly	0.2993***				
	(0.0894)				
R^2	0.63	0.3	0.33	0.29	0.34
N	50,164	119,582	140,067	124,624	124,624

Panel B: Impact of COVID-19 new case rate on new unemployment insurance claims, by subperiod

	[01.02–28.03]	[29.03–27.06]	[28.06–30.09]	[01.02–30.09]
COVID-19 new case rate weekly	29.0734***	0.9153***	−0.0536	0.6937***
	(6.2932)	(0.2834)	(0.0738)	(0.1511)
R^2	0.27	0.78	0.91	0.62
N	10,779	17,974	16,538	45,291

Panel C: Impact of COVID-19 new case rate on percent change in number of small businesses open, by subperiod

	[01.02–28.03]	[29.03–27.06]	[28.06–30.09]	[01.02–30.09]
COVID-19 new case rate daily	−0.0162***	−0.0007***	0.0005***	−0.0035***
	(0.0011)	(0.0000)	(0.0000)	(0.0001)
R^2	0.22	0.54	0.84	0.28
N	28,541	40,857	41,307	110,705

Panel D: Impact of COVID-19 new case rate on percent change in net revenue for small businesses, by subperiod

	[01.02–28.03]	[29.03–27.06]	[28.06–30.09]	[01.02–30.09]
COVID-19 new case rate daily	−0.0217***	−0.0004***	−0.0000	−0.0034***
	(0.0015)	(0.0001)	(0.0000)	(0.0000)
R^2	0.21	0.52	0.79	0.32
N	28,541	40,857	41,307	110,705

Note: This table presents estimates of a linear regression where a dependent variable is a weekly change in an economic indicator and an explanatory variable is the weekly number of new COVID-19 cases per 100,000 people. The economic indicators are: (1) Count of initial unemployment insurance claims; (2) employment level for workers in the bottom quartile of the income distribution (incomes approximately under $27,000); (3) employment level for workers in the middle two quartiles of the income distribution (incomes approximately $27,000–$60,000); (4) number of small businesses open calculated as a 7-day moving average seasonally adjusted and indexed to January 4–31, 2020; (5) net revenue for small businesses, calculated as a 7-day moving average, seasonally adjusted, and indexed to January 4–31, 2020. Panel A reports the estimates for the whole time period from February 01, 2020 to October 31, 2020 for 3143 US counties. Panels B–D report subperiod estimates for the indicators (1), (4), and (5), respectively. County fixed effects are included but not reported for brevity. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

range of plausible frequencies. In terms of its global impact, COVID-19 can be compared with the Spanish Flu outbreak in 1917, which is consistent with the 1-in-100 years frequency. We use the 1-in-100 years frequency as a baseline and extend the estimation to alternative frequencies of 1-in-50 and 1-in-20 years to assess the sensitivity of the estimates.

Given the baseline assumptions that the contract provides coverage for the basic income of \$2000 for 12 months, the insurer's per contract loss payment is \$24,000. Then, using the predicted new unemployment cases caused by the rise of the infection rate in each county in the United States, we can estimate the total new claims and the claim costs as a function of the infection rate. Results in Table 5 Panels B–D show that most new unemployment cases caused by the pandemic occurred during the initial phase in February–June 2020. Therefore, we calibrate the loss distribution of the hypothetical insurance contract using the new unemployment claims reported during February–June 2020.

Under the baseline assumptions, the parameters of the fitted log-normal distribution of pandemic insurance contract losses are $\mu = 29.95$ and $\sigma = 1.59$. Table 6 Panel A reports the statistical characteristics of the loss distribution for the baseline monthly payout of \$2000, and for two alternative less-generous contract monthly payouts of \$1000 and \$1500. The losses of the hypothetical contract are reported on the aggregate industry basis. For the baseline case of \$2000, the estimated standard deviation of \$1.77 million and the estimated expected shortfall of \$4.6 trillion are the aggregate insurance industry loss distribution characteristics if the small-business workers held the hypothetical unemployment insurance contract before the pandemic. The estimated expected shortfall reduces by around \$1 trillion for each of the \$500 reduction in the monthly payout. To illustrate the role of pandemic frequencies on the tail characteristics of the loss distribution, Table 6 Panel B reports the tail statistics for the baseline payout of \$2000 with different frequencies. These findings show that increasing the frequency of the loss from 1-in-100 to 1-in-20 years multiplies the expected shortfall estimates by seven times, from \$4.6 trillion to \$32.4 trillion.

4.3.2 | Calibration of the pandemic insurance contract markup

To estimate the markup of the pandemic insurance contract using the catastrophe risk pricing models (4) and (5), we need to allocate the industry-wide loss distribution to individual insurers. We consider the market shares of 1%, 2%, and 3% of the exposure. These market shares correspond to the actual market shares of larger property–casualty insurance groups in the NatCat risk market with assets above \$4 billion.

Table 7 reports the allocated insurer-level expected shortfalls as well as the estimated price markup using the pooled model of catastrophe risk lines and the industry average rating of 2.97 equivalent to A rating, for individual insurers with market shares varying from 1% to 3% in case of the baseline payout of \$2000. The estimated markup for these market shares ranges between 4.5 and 5, meaning that the contract requires a premium of 4.5–5 times higher than the expected loss. These estimates correspond to the top 20% of the observed markups in the NatCat risk insurance market.

The results are illustrated in Figure 1. The red segment in Figure 1 depicts the range of expected shortfall and the corresponding markup for monthly payout amounts of \$2000 for an insurer covering between 1% and 3% of this hypothetical market, obtained using the estimates of (4) and (5) and the 1% expected shortfall of the pandemic loss distribution. The cloud of blue dots represents the values of the markups and the expected shortfalls for insurers in the sample.

TABLE 6 Characteristics of loss of the hypothetical contract given the COVID-19 pandemic loss

Panel A: Characteristics of loss of the hypothetical contract industry wide, for different payout		
Contract payout ($)	**SD (trillion $)**	**$ES_{1\%}$ (trillion $)**
2000	1.77	4.6
1500	1.32	3.5
1000	0.88	2.3
Panel B: Characteristics of loss of the hypothetical contract industry wide, for different pandemic frequency		
Frequency	**SD (trillion $)**	**$ES_{1\%}$ (trillion $)**
0.01	1.77	4.6
0.02	2.49	16.8
0.05	3.95	32.4

Note: This table presents the loss distribution of our hypothetical contact given the distribution of the number of unemployment claims. Note that we assume the contract to be triggered only in case of positive claims, therefore we exclude a negative predicted number of claims and this might lead to slightly overstated number of claims compared with the observed ones. Panel A shows figures for our baseline contract with a payout of $2000 and for contracts with a payout of $1500 and $1000 for comparison. Panel B compares the loss characteristics of our baseline contract estimated for a pandemic frequency of 0.01 with its loss if the pandemic frequency is assumed 0.02 and 0.05.

TABLE 7 Insurer level expected shortfall and estimated markup

Market share (%)	$ES_{1\%}$ (billion $)	Est. Markup $(1+\lambda)$	Quantile (%)
3	138	5.17	19.64
2	92	4.88	20.78
1	46	4.41	22.76

Note: This table presents the expected shortfall for a confidence level of 1% and estimated markup for firms covering a market share of 1%, 2%, and 3% of our hypothetical pandemic unemployment insurance market. The markup has been estimated assuming the average rating in our data set, 2.97133 (A). The last column places the estimated markup in the distribution of markups in our sample and shows what percentage of markups in our sample are higher than the estimated markup for pandemic unemployment insurance.

Figure 1 shows that the expected shortfall of the pandemic loss distribution is higher than the typical shortfall of NatCat losses. Thus, the markup that the insurers would require to provide coverage for pandemic losses will also be higher.

Several other factors are important to consider for the assessment of the potential private market for pandemic insurance. One factor is the allocation of losses among individual insurers and the impact of the pandemic insurance payouts on insurers' solvency. The estimation of the pricing of catastrophic risk shows that only 41% of the variation in the markup is explained by the expected shortfall in the pooled regressions with all business lines, Table 3 Panel A, while the rating is not a significant factor in this estimation. By contrast, the line of business analysis of the markup reported in Table 3 Panel B reveals that there is a significant effect of credit ratings for the commercial lines of insurance, like, commercial multiple peril and special property. The elasticity of the markup to ratings is similar and sometimes higher than the elasticity to expected shortfall.

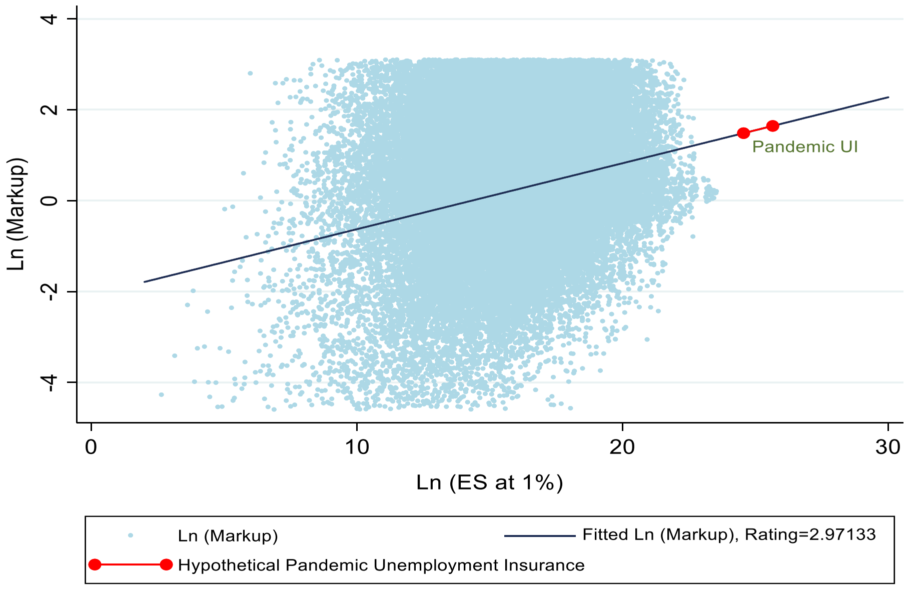

FIGURE 1 Markup as a function of expected shortfall, log–log regression. This figure plots the fitted regression line of the logarithmic of markup, given the logarithmic of the expected shortfall of the loss distribution at 1% and fixing rating to the average in our data set, 2.97133. The red segment represents the Hypothetical Pandemic Unemployment Insurance contract burden for firms with a market share of 1%–3%

Only a dozen of insurance firms in our data set has net assets of the same range as the calibrated expected shortfall for an insurer with 1% market share in pandemic insurance market. The reason is that the expected shortfall for the calibrated pandemic insurance is approximately 50–100 times higher than the expected shortfall of a NatCat event estimated in any of the regions on industry aggregate level. The density of losses of the severity distribution of the pandemic insurance contract is significantly more concentrated in the right tail compared with the density function of the distribution of NatCat losses. Therefore, supply of pandemic insurance can be limited due to the impact of pandemic risk exposures on companies' insolvency risk.

Another consideration is that the demand for catastrophe insurance is sensitive to income. Therefore, the excessive markups of the pandemic insurance contract can further reduce insurance coverage. Browne and Hoyt (2000) analyze the flood insurance market in the United States and find that income and price are influential factors in the decision to purchase flood insurance. Their estimates of the price elasticity of insurance demand range between 0.109 and 0.997. The income elasticity of demand is estimated between 1.506 and 1.400. Millo (2016) estimates the income elasticity of demand on the aggregate insurance market level and finds that the elasticity is around one. These factors are particularly relevant for designing pandemic insurance coverage for lower-income workers and for small- and medium-size businesses. Relatedly, our current analysis does not address the relationship between the insurance price and the take-up rate. On one side, making the pandemic insurance coverage mandatory by the government effectively would shift risk-bearing to the government instead of the insurance industry. On the other side, lower take-up rate would reduce the expected shortfall but would also make the pandemic insurance less meaningful.

Pandemic risk has several specific characteristics that distinguish it from the NatCat risk market which we use as a laboratory to calibrate the pandemic insurance markup. Unlike NatCat risk, pandemics have no geographic diversification. We address this concern by clustering of NatCat loss data to the regional level and using observations on regional level (firm–year–region line of business) in our main markup regression. Given that within a region NatCat losses tend to be highly correlated among states in the same region, the use of markup data on regional level improves comparability to pandemic risk.

In addition, pandemic is a systematic risk across multiple business lines, for example, event cancelation and workers compensation. Furthermore, the ability to measure the infection characteristics and spread speed relies on the public health system. Thus, the basis risk of the pandemic insurance contract will also depend on the reliability and effectiveness of the public health sector. Finally, unlike the NatCat events that are limited in time by geophysical factors, the stopping time of the pandemic depends on the investment in vaccine development as well as the geopolitics of vaccine distribution. These factors cannot be evaluated within our empirical framework, but they will be important for the pricing of pandemic insurance products.

More broadly, pricing pandemic insurance requires a new generation of pandemic risk models that are capable to model the link between the infection diseases characteristics, that is, number of fatalities, speed of transmission, and so forth, and their economic impact. Our approach of linking the economic indications and the infection rates to calibrate the loss distribution of a hypothetical pandemic insurance contract is a first step in this direction. Also, the models need to have sufficient resolution to price differences between the risks, for example, the price of insurance for essential and nonessential workers. Qiu (2020) discusses a few principles to establish credible pandemic models for the future. He argues that the COVID-19 insurance market environment is similar to the post-9/11. Before 9/11, terrorism models did not exist, and terrorism coverage was often included without charging an additional premium. But post-9/11, new models were developed and continue to improve, providing effective pricing of terrorism risk. Likewise, the COVID-19 experience has identified a vast amount of business opportunities for pandemic risk modeling and pricing.

5 | INTERTEMPORAL RISK-SHARING AND THE DESIGN OF THE PANDEMIC INSURANCE MARKET

Our findings demonstrate that high accumulation risk of pandemic losses and the lack of geographical diversification result in high insurance prices that will reduce the affordability of these contracts. On the basis of the recent experience of the insurance sector with COVID-19, OECD (2020) reports that, indeed, insurers are reducing or eliminating any potential coverage for pandemic risk in property damage and business interruption policies. This brings the question about the design of a risk-sharing mechanism that combines the expertise and the capacity of the insurance industry with those of the financial market and the public sector. Several such proposals are being discussed between the regulators and the insurance industry, for example, EIOPA (2020), The Geneva Association (2021), Klein and Weston (2020), and Kraut and de Kuiper (2021). Ultimately, many proposals involve enhancing the cross-sectional risk-sharing by insurers with an intertemporal risk-sharing mechanism either financed or guaranteed by the government. In this section, we analyze the scope for intertemporal risk-sharing to reduce the accumulation risk in the context of a hypothetical insurance contract.

Then we discuss some practical implementation challenges of a government-sponsored risk-sharing program.

We consider an intertemporal risk-sharing mechanism that facilitates pandemic risk pooling for 50 years. All insurers participate in the pool during the 50 years, and a long-term intermediary like a benevolent government can facilitate risk sharing. The setting is analogous to an Arrow–Debreu complete market environment and estimates the first-best potential of risk sharing. We come back to the most obvious challenges of arranging such scheme in practice later in this section.

The intermediary accumulates a fund by charging the reinsurance premiums to participating insurers. In the years of a pandemic, the intermediary disburses the fund. In case the accumulated fund is not sufficient to pay the reinsured losses, as would be the case if the next pandemic occurs in the early years of the scheme existence, the intermediary can borrow from the financial market to replenish the deficit. Insurers' participation in the scheme is compulsory.

The risk-sharing mechanism effectively enables to replace the loss distribution of the hypothetical insurance contract $\tilde{L}_t$ in year t with an average loss distribution across 50 years,

$$\tilde{L}_A = \frac{1}{50}\sum_{t=1}^{50} \tilde{L}_t.$$

Given the calibration of the pandemic insurance contract loss distribution in the cross-section $\tilde{L}_t$ reported in Section 4.3.1 and the frequency of 1-in-100 years, we simulate the loss distribution $\tilde{L}_A$ for an insurance contract with a \$2000 monthly payment. We apply the following procedure: First, we simulate a compounded loss distribution which is a mix of the 0.01 frequency and the log-normal severity distribution with parameters $\mu = 29.95$ and $\sigma = 1.59$. We simulate 50 values from this compounded distribution, corresponding to the 50 years stream of realized losses under the scheme. Next, we calculate an average of these realizations. By repeating the procedure 10,000 times, we obtain the distribution of the average loss and generate the distribution of the average loss. We obtain the 1% expected shortfall by calculating the mean of the lowest 100 realizations.

Given the 1% expected shortfall of the average loss distribution for the insurance industry, we obtain the company-level expected shortfall for an insurer with 1%, 2%, and 3% market shares as in our baseline analysis. The estimated insurer-level expected shortfalls for the range of market shares and the respective estimated markups are reported in Table 8. These results show that the estimated expected shortfall under the risk-sharing mechanism for an insurer with a 1% market share decreases from \$46 billion to \$23 billion. These estimates suggest that there is a significant reduction in the expected shortfall under the scheme. For comparison, an insurer with a 1% market share in NatCat coverage in Mid-Atlantic region faces the expected shortfall of 170 million USD (Table 1). However, the decrease in the expected shortfall translates only in a moderate reduction in price markup. This is the case because the elasticity of the markup to the expected shortfall estimated for the catastrophe risk market is only 0.1451.

Though our estimation results suggest potential benefits of the intertemporal risk-sharing, the practical implementation has several challenges. The first one is market incompleteness, arising from the voluntary entry and exit of insurance companies in the pandemic insurance market (Allen & Gale, 1997; Gordon & Varian, 1988). That is, the historic experience of the scheme with the occurrence of the pandemic can influence the insurers' entry and exit

TABLE 8 Risk-sharing mechanism

Market share (%)	$ES_{1\%}$ (billion $)	Est Markup $(1+\lambda)$	Quantile (%)
3	69.3	4.68	21.58
2	46.2	4.41	22.75
1	23.1	3.99	24.91

Note: This table presents the expected shortfall at 1% and estimated markup for firms covering a market share of 1%, 2%, and 3% of our hypothetical pandemic unemployment insurance market, under our proposed risk-sharing mechanism. The markup has been estimated assuming the average rating in our data set, 2.97133 (A). The last column places the estimated markup in the distribution of markups in our sample and shows what percentage of markups in our sample are higher than the estimated markup for pandemic unemployment insurance, under this risk-sharing mechanism.

incentives to the pandemic insurance market, even if insurers selling pandemic coverage are mandated to participate in the scheme.

Another issue of the scheme design is that it needs to preserve the insurers' incentives to price risk and to innovate suitable insurance products. The risk-sharing scheme has to establish a fine balance between reducing the exposure to the accumulation risk while retaining enough "skin in the game" for the private insurance market. Insurers' premiums to the scheme and the coverage should be risk-based. The scheme needs to recognize the trade-offs arising from asymmetric information and moral hazard in the insurance market in case of risk transfer from insurers to the scheme as a reinsurer (Doherty & Smetters, 2005). Furthermore, the collaboration of the public and the private sector creates a mix of stakeholders with divergent views and objectives (Jarzabkowski et al., 2018), including political pressure leading to short-termism.

Besides the challenges of designing an incentive-compatible long-term risk-sharing scheme, such a scheme can affect public health authorities and government preparedness to the pandemic as well as the actions during the next outbreak. Richter and Wilson (2020) suggest that if the economic costs of the containment measures are borne by the private insurance industry, the government has less incentives to remediate during the outbreak and is more willing to extend the containment measures. Furthermore, having the scheme in place can reduce government incentives to invest in public health system preparedness in terms of testing capacities, vaccine developments, and so forth.

In summary, our empirical analysis shows that an intertemporal risk-sharing scheme can add risk-bearing capacity for pandemic insurance. In the context of a hypothetical insurance contract, the scheme reduces the 1% expected shortfall by 50%. Complemented by the capacity of the external financial market, the scheme can provide a significant cushion to insured small businesses and their employees. However, the assessment provides a first-best estimate of risk-sharing capacity, and the scheme design is crucial to achieve it.

6 | CONCLUDING REMARKS

Our analysis of the scope of the private insurance market for pandemic risks shows that it is unlikely that the insurance industry alone will be able to provide sufficient coverage for business interruption losses like those occurring during the COVID-19 crisis. Compared with the NatCat insurance market, we show that the markup of a hypothetical insurance contract is in the top 20% of the realized price markups of NatCat insurance, and the expected shortfall of the loss distribution is about 100 times higher. We also explore the capacity of an intertemporal risk-sharing scheme to reduce the accumulation risk of the pandemic loss distribution and show that a scheme that enables risk-sharing over 50 years reduces the expected shortfall by 50%.

The experience of the COVID-19 crisis reveals the need for insurance products that link the pandemic characteristics to economic indicators like business revenue decreases and reduction in consumer spending. Our analysis is a first step in this direction, and it would not be possible without the high-frequency detailed OIT data. Our and other recent studies point out that a new generation of pandemic risk models can benefit substantially from big data analytic tools. The current digital revolution provides great opportunities for innovation.

Several important questions are left for future research. Our assessment of the scope for intertemporal risk-sharing takes the first-best approach. The design of the risk-sharing scheme that involves government and financial market investors needs to carefully consider the role of risk-based pricing and moral hazard. Appropriate risk mitigation incentives and state-of-the-art risk-based pricing are important components of the scheme. Ultimately, the scheme must find an optimal trade-off between enhancing the risk-bearing capacity and limiting the costs incurred by the taxpayers.

ACKNOWLEDGMENTS

Open Access funding enabled and organized by Projekt DEAL.

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How to cite this article: Gründl, H., Guxha, D., Kartasheva, A., & Schmeiser, H. (2021). Insurability of pandemic risks. *J Risk Insur*. 88, 863–902. https://doi.org/10.1111/jori.12368

APPENDIX A

In its first part Appendix A provides insights into the factors for pricing pandemic risks by applying the three-moments CAPM (Kraus & Litzenberger, 1976). On the basis of expected utility, the second part of Appendix A focuses on the demand for pandemic risk insurance, and determines the conditions under which a market for pandemic risk insurance is possible.

A.1 | Reservation price of the supply side

For shareholders of an insurance company (or any other investor who provides a similar risk coverage, for example, via Alternative Risk Transfer [ART] instruments), we assume that the assumptions of the three-moments CAPM hold true, especially that the capital market is in equilibrium and investors include the third moments of cash-flows in their portfolio choice. If the asset pricing formula derived for capital market instruments for arbitrage reasons also applies to insurance contracts, then, with points in time $t = 0, 1$, the insurance premium $P_{o,j}$ of policyholder j for (pandemic) claim payments $S_{1,j}$ is determined by[18]

$$P_{o,j} = \frac{1}{1 + r_{\mathrm{f}}}\left[E(S_{1,j}) - b_1 P_{0,j}\beta_{S_{1,j}} - b_2 P_{0,j}\gamma_{S_{1,j}}\right]. \tag{A1}$$

Thereby, b_1 denotes the market risk premium and b_2 the market skewness premium given by the relation $\mu_{\mathrm{M}} - r_{\mathrm{f}} = b_1 + b_2$, where r_{f} stands for the risk-free rate of return and μ_{M} for the expected rate of return of the market portfolio. Hence, the insurance premium in Equation (A1) is given by a risk-free discounted certainty equivalent that results from adjusting the expected claims payments by two terms that reflect systematic risk ($\beta_{S_{1,j}}$) and systematic skewness ($\gamma_{S_{1,j}}$). Before discussing the adjustment terms in detail, let us have a closer look at the market portfolio in the presence of pandemic risks.

Pandemic risks affect the value of the market portfolio. If we define V_1^i ($i = 1, \ldots, N$) as the future firm value of firm i, but without including pandemic losses, and S_1^i as the pandemic loss realizing in $t = 1$, then the value of the stochastic market portfolio W_1^{m} can be written as

$$W_1^{\mathrm{M}} = \sum_{i=1}^{N} V_1^i - S_1^i = W_1^{\mathrm{M}^*} - S_1^{\mathrm{M}}, \tag{A2}$$

$W_1^{\mathrm{M}^*}$ is therefore the future value of the market portfolio without pandemic loss, and S_1^{M} is the aggregate pandemic losses in the market. The rate of return of the market portfolio is therefore given by

$$r_{\mathrm{M}} = \frac{W_1^{\mathrm{M}}}{W_0^{\mathrm{M}}} - 1 = \frac{W_1^{\mathrm{M}^*} - S_1^{\mathrm{M}}}{W_0^{\mathrm{M}}} - 1, \tag{A3}$$

W_0^{M} is the present value of the market portfolio. We define the rate of return of the market portfolio without pandemic losses as $r_{\mathrm{M}^*} = \frac{W_1^{\mathrm{M}^*}}{W_0^{\mathrm{M}}} - 1$, and a "pandemic loss rate" R_{S} as the ratio between the

[18]Equation (A1) is a rearrangement of eq. (3) in Kraus and Litzenberger (1976), p. 1088, transferring their asset pricing formula (in rate-of-return notation) to the insurance context.

aggregate pandemic losses and the value of the market portfolio ($R_S = S_1^M / W_0^M$). The pandemic loss rate tells us which percentage of the market portfolio value gets lost through a pandemic. Hence, the rate of return of the market portfolio can be rewritten as

$$r_M = r_{M^*} - R_S. \tag{A4}$$

Let us discuss the risk adjustments in pricing formula (A1). The first adjustment term represents the market risk premium multiplied by the beta risk of the (pandemic) risk, and represents the traditional two-moments-CAPM markup for systematic risk. By using r_M from Equation (A4), and with $\sigma_M^2 = \mathrm{var}(r_M)$, the systematic risk is given by

$$P_{o,j}\beta_{S_{1,j}} = P_{o,j}\frac{\mathrm{cov}\left(\frac{S_{1,j}}{P_{o,j}} - 1, r_{M^*} - R_S\right)}{\sigma_M^2} = \frac{\mathrm{cov}(S_{1,j}, r_{M^*})}{\sigma_M^2} - \frac{\mathrm{cov}(S_{1,j}, R_S)}{\sigma_M^2}. \tag{A5}$$

The second adjustment term in Equation (A1) represents an adjustment for systematic skewness, that is, the market skewness premium multiplied by the coskewness of the insured risk with the market portfolio. The term $P_{o,j}\gamma_{S_{1,j}}$ can be rewritten as

$$\begin{aligned} P_{o,j}\gamma_{S_{1,j}} &= \pi_{o,j}\frac{\mathrm{cov}\left(\frac{S_{1,j}}{P_{o,j}} - 1, (r_M - \mu_M)^2\right)}{m_M^3} = \frac{\mathrm{cov}(S_{1,j}, (r_M - \mu_M)^2)}{m_M^3} \\ &= \frac{\mathrm{cov}(S_{1,j}, (r_{M^*} - R_S - (E(r_{M*}) - E(R_S)))^2)}{m_M^3} \end{aligned} \tag{A6}$$

with $m_M^3 = E[(r_M - E(r_M))^3]$.

Premium formula (A1) can now be written as

$$\begin{aligned} P_{o,j} = \frac{1}{1 + r_f}\Bigg[& E\left[S_{1,j}\right] - b_1\left(\frac{\mathrm{cov}(S_{1,j}, r_{M^*})}{\sigma_M^2} - \frac{\mathrm{cov}(S_{1,j}, R_S)}{\sigma_M^2}\right) \\ & - b_2\frac{\mathrm{cov}\left(S_{1,j}, \left(r_{M^*} - R_S - (E(r_{M^*}) - E(R_S))\right)^2\right)}{m_M^3}\Bigg]. \end{aligned} \tag{A7}$$

With a positive market price of systematic risk b_1 the sign of the premium charge regarding the sign of the first risk adjustment term is determined by the sign of the covariance terms.

The term $\frac{\mathrm{cov}\left(S_{1,j}, r_{M^*}\right)}{\sigma_M^2}$ reflects the traditional CAPM beta factor.[19] If the (pandemic) loss tends to be above average in times of below-average capital market returns, this leads to a negative covariance and gives rise for a systematic risk premium charge.

[19]Compare Fairley (1979).

The term $\frac{\mathrm{cov}(S_{1,j}, R_S)}{\sigma_M^2}$ reflects the cumulative risk coming along with pandemic risks. If the (pandemic) loss to be insured tends to be above average when the pandemic loss rate is also above average, that is, when the aggregate (pandemic) losses in relation to the present value of the market portfolio are above average, then a cumulative-risk-markup is the consequence. Investors of the insurance company require a compensation for such cumulative risk that worsens their financial situations in pandemic-related "bad times".

In the second risk adjustment term, as Kraus and Litzenberger show, b_2 has the opposite sign as the skewness parameter of the market portfolio rate of return m_M^3.[20] If $S_{1,j}$ and Y ($Y = (r_{(M^*)} - R_S - (E(r_{(M^*)}) - E(R_S)))^2$) are uncorrelated (negatively correlated), the second risk adjustment factor is zero (negative). A positive skewness markup results if $S_{1,j}$ and Y are positively correlated with $\mathrm{cov}(S_{(1,j)}, (r_{(M^*)} - R_S - (E(r_{(M^*)}) - E(R_S)))^2) > 0$. The latter case occurs if above-average loss payments prevail in situations of large deviations of the market portfolio return from its mean—which may be due to high pandemic loss rates R_S in otherwise normal capital market scenarios. The more extreme the losses are in situations of extreme capital market returns, the higher becomes the markup on the insurance premium. Thus, high cumulative risks, as reflected by a high R_S, can exacerbate the skewness markup through their effect in the market portfolio.

A.2 | Demand for pandemic risk insurance

Insurance customers are assumed to be risk-averse and not able to replicate their future cash-flows resulting from pandemic losses via assets traded on a frictionless and continuous capital market. Otherwise, there would be no economic reason for the existence of insurance. To determine the willingness to pay of an insurance customer, we refer to a representative customer focusing on her wealth position W_1 (we omit index j for simplicity reasons), which results from her stochastic asset endowment A_1 minus a stochastic (pandemic) loss S_1, if she purchases no insurance

$$W_1 = A_1 - S_1. \tag{A8}$$

In case she insures the pandemic risk (for the sake of simplicity only through full coverage) her final wealth position is given by

$$W_1 = A_1 - P_0^{\mathrm{gross}}. \tag{A9}$$

Hereby, $P_0^{\mathrm{gross}} = (1 + \lambda)P_o$, with P_o given by Equation (A7). The markup $\lambda > 0$ refers to the insurer's costs arising from financial market and regulatory frictions. We consider the following customer's preference function $\Phi(W_1)$ that is in line with maximizing expected utility, given an exponential utility function, and considering the first three moments of W_1[21]

[20]Compare Kraus and Litzenberger (1976), p. 1088. b_2 can be interpreted as market price of skewness, and reflects the appreciation of a positive skewness of returns by the capital market participants. As to Equation (A7), taking the positive sign of $\left(-\frac{b_2}{m_M^3}\right)$ into account, a positive skewness contribution of the cash-flow $S_{1,j}$ to the rate-of-return skewness of the market portfolio, expressed by a positive $\mathrm{cov}(S_{1,j}, (r_M - E(r_M))^2)$, therefore increases the cash-flow's equilibrium price.

[21]To stay in line with the desirable properties of a utility function as specified by Arrow (1970) we choose a utility function that displays the same rates of substitution as the Taylor approximation of the negative exponential utility function $U = -e^{-aW}$, that is, $ad\mu - \frac{1}{2}a^2 d\sigma^2 + \frac{1}{6}a^3 d\gamma = 0 \geq \frac{d\mu - \frac{1}{2}ad\sigma^2}{d\gamma} = -\frac{1}{6}a^2$.

$$\Phi(W_1) = E(W_1) - \frac{a}{2} \cdot \sigma^2_{W_1} + \frac{a^2}{6} \cdot \gamma_{W_1}, \tag{A10}$$

$\sigma^2_{w_1}$ stands for the variance of the wealth position of the customer $\text{var}(W_1)$, and γ_{W_1} for its skewness. Moreover, the risk aversion parameter is $a > 0$.

For the insurance policy to be attractive, the preference value from buying the policy should be higher than the preference value if no insurance is purchased.

With $\sigma^2_{A_1} = \text{var}(W_1)$ and $\sigma^2_{S_1} = \text{var}(S_1)$ we obtain in the case without insurance the expected wealth, its variance and skewness

$$E(W_1^{\text{w/o}}) = E(A_1) - E(S_1), \tag{A11}$$

$$\sigma^2_{W_1^{\text{w/o}}} = \sigma^2_{A_1} + \sigma^2_{S_1} - 2\text{cov}(A_1, S_1), \tag{A12}$$

$$\gamma_{W_1^{\text{w/o}}} = \frac{E((A_1 - S_1)^3) - 3E(A_1 - S_1)\sigma^2_{A_1 - S_1} - (E(A_1 - S_1))^3}{\left[\sigma^2_{A_1} + \sigma^2_{S_1} - 2\text{cov}(A_1, S_1)\right]^{3/2}}. \tag{A13}$$

By setting $r_f = 0$ and substituting the sum of the risk adjustment terms in Equation (A7) by R_{adj}, the first two central moments and the skewness of the wealth distribution with full coverage are given by

$$E(W_1^{\text{with}}) = E(A_1) - (1 + \lambda)(E[S_1] + R_{\text{adj}}), \tag{A14}$$

$$\sigma^2_{W_1^{\text{with}}} = \sigma^2_{A_1}, \tag{A15}$$

$$\gamma_{W_1^{\text{with}}} = \frac{E(A_1{}^3) - 3E(A_1)\sigma^2_{A_1} - (E(A_1))^3}{[\sigma^2_{A_1}]^{3/2}}. \tag{A16}$$

Purchasing insurance is advantageous if $\Phi(W_1^{\text{with}}) - \Phi(W_1^{\text{w/o}}) > 0$. In formal terms, we have

$$\Phi(W_1^{\text{with}}) - \Phi(W_1^{\text{w/o}}) = -\lambda E[S_1] - (1 + \lambda)R_{\text{adj}} + \frac{a}{2}(\sigma^2_{S_1} - 2\text{cov}(A_1, S_1)) + \frac{a^2}{6}(\gamma_{W_1^{\text{with}}} - \gamma_{W_1^{\text{w/o}}}) > 0. \tag{A17}$$

APPENDIX B

TABLE B1 List of publicly traded insurance groups

	P&C Insurance Group
1	Bank of America Corporation (SNL P&C Group)
2	First Acceptance (SNL P&C Group)
3	Allstate Corp (SNL P&C Group)
4	The Cincinnati Insurance Cos. (SNL P&C Group)
5	National Security Group Inc. (SNL P&C Group)

(Continues)

TABLE B1 (Continued)

	P&C Insurance Group
6	Kemper (SNL P&C Group)
7	AIG (SNL P&C Group)
8	W. R. Berkley Corp. (SNL P&C Group)
9	Horace Mann (SNL P&C Group)
10	Mercury Insurance (SNL P&C Group)
11	Progressive (SNL P&C Group)
12	United Fire Group Inc. (SNL P&C Group)
13	Old Republic Insurance (SNL P&C Group)
14	Hallmark (SNL P&C Group)
15	Chubb (SNL P&C Group)
16	American National (SNL P&C Group)
17	Great American Insurance (SNL P&C Group)
18	Selective (SNL P&C Group)
19	Berkshire Hathaway Inc. (SNL P&C Group)
20	The Hanover Insurance Group (SNL P&C Group)
21	The Hartford (SNL P&C Group)
22	General Electric Co. (SNL P&C Group)
23	AXA SA (SNL P&C Group)
24	QBE (SNL P&C Group)
25	Fairfax Financial (SNL P&C Group)
26	AMERCO (SNL P&C Group)
27	Universal Insurance Holdings Inc. (SNL P&C Group)
28	Zurich (SNL P&C Group)
29	Markel (SNL P&C Group)
30	MetLife (SNL P&C Group)
31	Travelers (SNL P&C Group)
32	Safety Insurance (SNL P&C Group)
33	AXIS (SNL P&C Group)
34	MAPFRE (SNL P&C Group)
35	Hiscox Ltd. (SNL P&C Group)
36	Global Indemnity (SNL P&C Group)
37	Assurant (SNL P&C Group)
38	Tokio Marine (SNL P&C Group)
39	Beazley Plc (SNL P&C Group)
40	Allianz (SNL P&C Group)
41	Houston International Insurance (SNL P&C Group)

TABLE B2 Estimated market betas for P&C insurers yearly

P&C Insurer	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
AIG	0.796	0.667	1.215	1.398	1.144	1.002	0.860	1.142	2.281	1.945	1.531
Allianz	0.258	0.598	1.269	1.506	0.786	0.434	1.122	0.654	0.640	1.132	0.977
Allstate Corp	0.901	0.497	0.563	0.678	0.799	0.796	0.715	0.902	1.301	1.778	1.141
AMERCO	0.419	0.433	1.046	0.090	1.218	1.458	2.312	1.640	0.957	1.601	1.463
American National	0.381	0.338	0.236	0.356	0.170	0.107	0.178	0.447	1.510	1.680	1.217
Assurant					0.410	0.713	0.666	0.874	1.277	1.714	1.018
AXA SA	0.352	0.680	1.065	1.146	0.749	0.460	1.159	0.843	0.842	1.375	1.711
AXIS					0.606	0.705	0.714	0.527	0.992	1.098	0.777
Bank of America Corporation	1.087	1.000	0.949	0.772	0.823	0.840	0.845	1.108	1.871	3.140	1.576
Beazley Plc				−0.120	−0.051	−0.078	0.288	0.769	0.457	0.444	0.532
Berkshire Hathaway Inc.	0.548	0.338	0.291	0.265	0.304	0.226	0.285	0.267	0.555	0.812	0.817
Biglari Holdings Inc.	0.112	0.676	0.815	0.930	1.236	1.588	1.392	0.763	0.961	1.449	0.925
Chubb	1.009	0.940	0.978	1.200	1.000	1.082	1.074	1.051	1.101	1.122	0.762
Fairfax Financial	0.365	0.268	0.276	0.960	0.530	0.382	0.862	0.423	0.119	0.557	0.485
First Acceptance	0.030	0.258	0.053	0.244	1.056	1.099	1.534	1.219	1.337	1.741	0.840
General Electric Co.	1.027	1.542	1.357	1.108	1.089	0.890	0.764	0.911	1.053	1.475	1.246
Global Indemnity					0.232	0.240	0.561	1.000	0.897	1.839	1.683
Great American Insurance	0.476	0.545	0.916	0.775	0.769	0.764	0.873	0.984	1.531	1.364	1.039
Hallmark	0.181	−0.232	0.277	0.511	−0.710	0.030	−0.716	0.949	0.495	0.766	1.219
Hiscox Ltd.	−0.124	0.687	−0.058	−0.195	0.207	−0.040	0.844	0.606	0.207	0.543	0.352
Horace Mann	0.997	0.720	0.763	0.853	0.933	1.378	1.420	1.374	1.686	1.792	1.425
Houston International Insurance	0.759	1.037	0.685	0.247	1.115	0.138	1.164	−0.233	0.323	0.244	0.928
Kemper	0.472	0.598	0.674	0.923	1.113	0.941	0.969	1.081	1.277	1.721	1.455
MAPFRE	0.153	0.037	0.202	−0.031	0.574	0.225	0.714	0.517	0.553	0.879	1.379
Markel	0.555	0.558	0.354	0.378	0.426	0.387	0.448	0.503	1.185	1.275	0.745
Mercury Insurance	0.505	0.300	0.537	0.567	0.666	0.790	0.859	0.731	1.006	1.042	0.713
MetLife		0.719	0.883	0.995	0.996	1.085	1.079	1.309	1.600	2.784	1.525

(Continues)

TABLE B2 (Continued)

P&C Insurer	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
National Security Group Inc.	0.244	0.085	−0.100	0.132	0.159	−0.112	0.206	0.058	0.391	0.129	−0.111
Old Republic Insurance	0.608	0.529	0.719	0.885	0.682	0.883	0.767	1.003	1.493	1.377	1.077
Progressive	1.151	0.605	0.737	0.863	0.863	0.963	0.692	0.751	1.103	1.278	1.018
QBE	0.077	0.710	−0.083	−0.140	0.210	−0.061	0.305	0.355	0.257	0.640	0.571
Safety Insurance				0.528	1.151	1.409	1.012	1.109	0.854	0.989	0.790
Selective	0.199	0.873	0.697	0.827	1.264	1.469	1.282	1.549	1.254	1.464	1.050
The Cincinnati Insurance Cos.	0.800	0.513	0.750	0.909	0.773	0.936	0.720	1.124	1.357	1.217	1.001
The Hanover Insurance Group	0.591	0.689	0.947	1.481	1.570	1.072	0.948	0.880	0.974	0.861	0.676
The Hartford	1.171	0.737	1.020	1.302	1.115	1.205	1.096	1.247	1.638	3.438	1.801
Tokio Marine				−0.011	0.404	−0.181	0.358	−0.096	0.008	0.016	−0.071
Travelers	0.788	0.714	0.926	1.013	1.161	0.973	1.034	1.039	1.266	0.984	0.711
United Fire Group Inc.	0.257	0.238	0.515	0.792	0.841	0.931	0.845	1.277	1.377	1.562	1.260
Universal Insurance Holdings Inc.	−0.434	0.681	−1.457	0.496	0.600	−0.344	1.223	0.953	0.712	0.654	0.655

Note: This table presents estimates of market beta for each insurer in our sample, yearly. Betas have been estimated based on daily returns over 1 year, with a minimum of 200 observations per insurer, per year. The estimation is based on an OLS regression controlling for interest rate; we use the US 10-year constant maturity note yield to control for interest rate and the S&P 500 Index as a proxy for the market portfolio. The estimates for market beta are found to be statistically significant.