Insurability of Pandemic Risks

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Abstract

The paper analyzes the scope for the private market for pandemic insurance and discusses the potential role of the financial market and the government. Building on a premise that pandemics are classified as catastrophic risks by the insurance industry, we start by providing a framework that explains theoretically how the catastrophe insurance supply and demand depend on the skewed and fat-tailed loss distributions and the co-movement between insurance stocks performance and the financial market. We use the model to estimate the supply of insurance for natural catastrophes. Then, by using the high-frequency data that tracks the economic impact of the COVID-19 pandemic in the US, we calibrate the loss distribution of a hypothetical insurance contract designed to alleviate the impact of the pandemic on small businesses and employment. The model of catastrophic insurance supply provides a calibration of the supply of pandemic insurance and allows us to compare it to other types of catastrophic insurance. Building on our estimation results, we discuss the scope for the risk transfer to the financial market and the role of the government.

Keywords: pandemic insurance, catastrophe risk transfer, private-public partnerships

JEL Codes: G22, G28, G32, J65, H84, Q54

I. Introduction

The economic losses of COVID-19 pandemic are estimated at 4.4% contraction of the global GDP in 2020 (IMF, October 2020). Business disruptions have been devastating in some sectors of the economy, particularly for small and medium size enterprises in areas with in-person interactions as in tourism[1]. In addition, the natural science consensus about the growing frequency of emerging infectious diseases (Jones et al., 2008; Smith et al., 2014; WEF, 2019) suggests that the risk of global pandemics will remain after the COVID-19 crisis is over. How can 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 address these questions by building a model that explains how supply and demand of catastrophe insurance depend on the correlated tail risks that capture the distinctive characteristics of the pandemic losses and stock market downturns during the pandemic. The main insight of the model is that the ability of insurers to carry risks is problematic for asymmetric loss distributions if loss skewness is correlated with the stock market skewness. Then we estimate a model of catastrophe insurance pricing depending on the volatility and fatness of the tail of the loss distribution and the correlation of the insurers' returns with the stock market. The model is used to calibrate the supply of a hypothetical pandemic insurance contract designed to alleviate the impact of the pandemic on small and medium businesses revenues and employment. We estimate the loss distribution of the pandemic insurance contract using the high-frequency private companies' data that tracks the economic impact of COVID-19 pandemic on county level in the US reported in (Chetty et al., 2020b).

Our concept of insurability is based on the existence of positive gains from trade between an insurer and a policyholder, i.e. the situation where the minimum premium acceptable to an insurer is lower than a potential policyholder's willingness to pay. We show that insurability is harder to achieve the higher is the correlation of skewness of asymmetric loss distributions. The lack of insurability is the motivation for proposing public-private partnerships for offering pandemic insurance solutions – either as traditional insurance products or via risk securitization. We discuss the implications of our results for the design of such partnerships for pandemic risks, in light of the previous literature on catastrophe risk financing and the practical experience of public-private partnerships for other tail risks like earthquakes, floods and terrorism.

Our theoretical model applies the three-moments CAPM developed by Kraus and Litzenberger (1976) to compare the equilibrium prices for pandemic risk insurance contracts with the maximal willingness to pay for purchasing such a coverage. Including the third

[1] See, e.g., the reports of the World Tourism Organization (www.unwto.org) on the impact of Covid-19

central moments of the claim distribution into the analysis allows us to adequately map "low frequency – high severity" situations, as they are typical for pandemic 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 premiums reflects the cumulative risk character of pandemic risks that affect many policyholders at the same time. Investors of insurance companies require a compensation for assuming risks that occur in situations in which many other claims lower their wealth. In addition, the "co-skewness" of pandemic risks with capital market risks and insurance risks influences the price for insurance.

We derive the maximal willingness to pay for a potential policyholder from the same expected utility framework that underlies the three-moments CAPM. Thus, we also take effects of skewed distributions on the demand side into account. Moreover, the policyholder's stochastic basis income is modelled to accommodate different interrelations between the policyholders' claims resulting from a pandemic and her wealth position. We elaborate under which conditions a market for pandemic risk is possible. In essence, this is an evaluation of advantages of the risk transfer to an insurer with the disadvantages stemming from pandemic-specific surcharges, arising from cumulative risk and skewness effects, on the insurance premium.

Building on the main insights of the model that catastrophe insurance pricing is driven by the characteristics of the loss distribution and the co-movement of the insurer's stock returns with the stock market index, we calibrate the pandemic insurance market empirically. Our objective is to evaluate the supply and the demand 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 which were hit particularly hard by COVID-19. The contract provides a fixed monthly compensation during the pandemic for either the lost revenues of the business or for the lost employment income of its workers.

Assessment of the market for the hypothetical pandemic insurance contract consists of two parts. First, it requires the calibration of the distribution of losses for small and medium businesses revenues and employment triggered by the pandemic. Second, it involves the empirical estimation of the model that explains, in line with our theory, how the supply and the demand of (any) catastrophe insurance depend on the characteristics of the loss distribution and the co-movement of insurer's returns with the stock market. Then, the pandemic insurance market can be calibrated by evaluating the supply and the demand of the estimated models for catastrophic risk induce by the specific pandemic loss distribution and the co-movement of insurers' stock returns and the market index during COVID-19 pandemic in 2020.

Our analysis of the loss distribution during the pandemic builds on the data collection and research of the Opportunities Insights Team (OIT) presented in (Chetty et al., 2020b). They build a publicly available platform that provides data on business revenues, business closures, employment, and consumer spending at a high frequency granular (county or zip code) level in the US, among other data. OIT data is obtained in anonymized form from private companies such as credit card processors, payroll firms, and financial services firms. (Chetty et al., 2020a) analysis of the data uncovers that the initial reduction in GDP following COVID-19 shock came from reduced spending by high-income households. Most of the reduction in spending occurred in sectors with in-person interaction like hotels, transportation, and food services. 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, compared to 30% in less affluent areas. As businesses lost revenues, they reduced employment, particularly for low-wage employees.

Our design of a hypothetical pandemic contract is motivated by (Chetty et al., 2020a) findings. We consider an insurance contract that would compensate the lost revenue of income because of the pandemic due to the collapse of demand for in-person services. Furthermore, we exploit OIT data to 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 US, we calibrate the aggregate loss distribution were these losses to be insured. This estimation provides an assessment of the severity of pandemic losses to small businesses and their employees.

To assess how the insurance market prices pandemic insurance for the aggregate loss distribution, we need a model of catastrophe insurance pricing depending on the characteristics of the loss distribution and co-movement of insurance stock returns with the market portfolio. On the supply side, we estimate such a model for the homeowner and farm-owner insurance market in the US using the insurance companies regulatory reporting to the NAIC. Among other perils, these policies provide protection from losses induced by natural catastrophes like earthquakes, hurricanes, winds, fire, and floods.

Consistent with Sommer (1996) and Cummins and Danzon (1997), we derive the insurance price markup as the ratio between the direct premiums written and the discounted paid losses and other expenses obtained from Schedule P annual reporting for the subsequent 10 years following the accident year. We rely on the loss distributions estimation across various US regions and perils from Froot and O'Connell (2008). We estimate the insurer's exposure to these loss distributions by using the state level data on their direct premiums written in homeowner and farmowner insurance. Then, based on exposures for each insurer-year, we construct the volatility and the fatness of the tail of the loss distribution. In addition, we obtain

the insurers' annual betas by estimating a standard two-factor CAPM for publicly traded insurers (Hartley et al., 2016).

The estimation of the catastrophe insurance pricing model reveals that the markup charged for insurance coverage with exposure to catastrophic losses is higher for losses with higher expected shortfall, i.e. distributions with higher tail risk, as predicted by the theory. A 10% increase in the expected shortfall translates in 2.2% increase in the markup. We also find that the markup is not significantly driven by the insurers' betas with the stock market. The latter finding is consistent with the limited economic impact of natural hazards on the US economy.

Our estimation of the catastrophe insurance supply could be extended in several dimensions. While the advantage of relying on the loss distributions reported in Froot and O'Connell (2008) is the simplicity, their loss distribution estimates combine states in regions with extensive geographical coverage. Using a higher granularity data like the SHELDUS™ would allow to increase the precision of the loss distribution estimation to the state level. Furthermore, our analysis could be extended to other catastrophe lines of business.[2]

Combining the estimated catastrophe insurance pricing model and the calibrated loss distribution of the hypothetical insurance contract allows us to calibrate the markup for pandemic insurance. Our main result is that the markup of the pandemic insurance contract is substantially higher compared to the markups insurers charge for insurance with exposure to natural catastrophes. The estimated markup corresponds to the top quantile of the markups charged for the catastrophe insurance. Strong correlation among claim demands across different geographies and clustering of claims at the first phase of the occurrence of the pandemic result in a large expected shortfall of the pandemic loss distribution which translates in high insurance price markup.

Turning to the demand side, the calibration of the demand function builds on the literature that estimates the individual demand for catastrophic insurance and the income elasticity of demand. Browne and Hoyt (2000) analyze the financial performance of the US National Flood Insurance Program to estimate how flood insurance demand depend on the price of coverage and the income of perspective policyholders. Millo (2016) develops an aggregate analysis of the non-life insurance market and concludes that insurance is a normal good, i.e. with elasticity of demand less than one. The implication of these findings is that the demand for pandemic insurance will be overly sensitive to the insurance price which may be a hurdle for insurance uptake for small and medium businesses or their workers.

[2] The other lines of business with exposure to catastrophe losses are Commercial Auto Physical Damage, Multiple Peril (Non-Liability), Earthquake, Federal Flood, Fire, Inland Marine, Multiple Peril Crop, Private Passenger Auto Physical Damage, Private Crop, and Private Flood.

In summary, our results suggest that though there can be some scope for private insurance market for business interruption losses generated by the pandemic, it may be limited and not sufficient to cover the losses comparable to those experienced by businesses in sectors with in-person interaction during the COVID-19 episode. This brings the questions about the scope for risk-transfer to the financial market and the role of the government. In the last past of the paper, we present an overview of the current proposals for public-private partnership put forward by regulators and insurance industry in several countries. Our analysis can be further extended to assess the merits of these proposals.

The remainder of the paper is organized as follow. Section II gives a short overview on related literature. In Section III we derive the conditions for the existence of a market for pandemic insurance. In Section IV we present a special case of the insurability conditions using simplifying assumptions. The empirical calibration of the model is provided in Sections V-VII. In section VIII we discuss the Implications for the Design of the Pandemic Insurance Market. Section IX concludes.

II. Related Literature

The present contributes to three strands of the literature. Our analysis addresses the issue of insurability which has a long tradition in the insurance literature. Also, we contribute to the literature on the financing of catastrophe risks, though previously the primary focus of that literature has been on weather related hazards and earthquakes. Finally, our analysis is related to the contemporaneous and fast-growing literature assessing the impact of COVID-19 on the economy and the design of policies to facilitate the economic recovery.

The issue of insurability has always been at the core of the insurance literature. A 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. Based on an insurer's strategic objectives, Berliner and Bühlmann (1986) and Nierhaus (1986) set up a framework to analyze for which risks a (re)insurer would offer coverage. Schmit (1986) clarifies that a decisive requirement of insurability is predictability of the insurer's loss portfolio. McNichol et al. (2000) argue that 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.

Our analysis discusses the limits of the ability of the private insurance market to bear the risks of rare events with large losses which has been the focus of the literature of the catastrophe risk financing. The key insights of this literature (Cummins et al., 2002; Niehaus, 2002; Froot and Posner, 2000; Froot, 1999; Jaffee and Russell, 1997; Froot, 2001) are that providing

insurance for large financial losses caused by catastrophes involves intense risk-sharing within the insurance industry by the means of reinsurance and retrocession. But the capacity of the industry is limited by the aggregate size of equity capital. Thus, insuring low probability/ large loss risks may also require risk-transfer outside the insurance industry to the financial market, for example, through securitization (Cummins and Trainar, 2009; Doherty, 1997). However, perfect risk sharing is still unlikely due to agency problems and capital market imperfections (Jaffee and Russell, 1997; Froot, 2007, 2008; Froot and O'Connell, 2008). Because of these imperfections, the private insurance industry may have limitations of sharing catastrophe risk over-time. In principle, the government could play a role of a long-term agent providing the diversification over time. However, the analysis of a number of government programs for catastrophe risk financing by Cummins (2006) and Jaffee and Russell (1997) reveal the political pressure, operational inefficiencies, undercapitalization and market distortions associated with these programs.

Our theoretical framework applies the three-moment CAPM proposed by Kraus and Litzenberger (1976) which accounts for skewness when setting the required return from an investor perspective. While there has been criticism on the three moment CAPM (Post et al., 2008; Dertwinkel-Kalt and Köster, 2019), it is a widely acknowledged pricing approach (see for example Langlois (2020)) that seems to be especially suited for pricing insurance for "low frequency-high severity" loss distributions. To be consistent between the supply and demand side, we employ a utility function for the insurance customer that takes skewness into account in line with Tsiang (1972; Mitton and Vorkink); Mitton and Vorkink (2007) and Kraus and Litzenberger (1976).

The literature on the economic impact of the COVID-19 pandemic and its insurability has been expanding rapidly during 2020. Examples for the economic-impact literature are Ashraf (2020), Gollier and Gossner (2020), Gollier (2020a, 2020b, 2020c). The question of insurability of pandemic risks is addressed in Richter and Wilson (2020). In their assessment, the limits of insurability pandemic risks lie in the large loss accumulation through pandemic insurance, and in "external moral hazard". The latter refers to the incentive to decrease public containment activities for mitigating the consequences of a pandemic outbreak if policymakers know about a sufficient private insurance coverage.

III. Theoretical Conditions for the Existence of an Insurance Market for Pandemic Risks

In a functioning insurance market, the price required by the supply side must not exceed the willingness to pay on the demand side. In what follows, we analyze whether risks exhibiting

pandemic properties can be insured. For this, we compare the premium required by an insurance provider based on the three-moments CAPM of Kraus and Litzenberger (1976) and the maximal willingness to pay of a representative policyholder based on a utility function that likewise accounts for skewed cash-flow distributions. As catastrophic risks in general have a specific "low frequency-high severity" property, its skewness impact on pricing can be estimated by taking the third moment of the loss distribution into account, in addition to the traditional two-moments CAPM approach.

Reservation price of the supply side

For shareholders of an insurance company (or any other investor who provides a similar risk coverage, e.g., via Alternative Risk Transfer (ART) instruments), we assume that the assumptions of the three-moments CAPM (Kraus and Litzenberger, 1976) 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 $\pi_{o,j}$ of policyholder j for a (pandemic) risk $S_{1,j}$ is determined by

$$\pi_{o,j} = \frac{1}{1+r_f}\left[E\left[S_{1,j}\right] - b_1\pi_{0,j}\beta_u - b_2\pi_{0,j}\gamma_u\right] \tag{1}$$

Thereby, b_1 denotes the market risk premium and b_2 the market skewness premium given by the relation $\mu_m - r_f = b_1 + b_2$, where r_f stands for the risk-free rate of return and $\mu_m = E(r_m)$ for the expected rate of return of the market portfolio. Hence, the insurance premium in Equation (1) is given by a risk-free discounted certainty equivalent that results from adjusting the expected claims payments by two terms.

Insuring pandemic risks by stock insurers alters the value of the market portfolio. For this, we define the value of the stochastic market portfolio W_1^m in t = 1 as

$$W_1^m = x'P_1 - S_1 \tag{2}$$

The rate of return of the market portfolio is therefore given by

$$r_m = \frac{W_1^m}{W_0^m} - 1 = \frac{x'P_1 - S_1}{W_0^m} - 1 \tag{3}$$

Let us define the rate of return of the market portfolio without pandemic losses with

$$r_{m*} = \frac{x' P_1}{W_0^m} - 1 \tag{4}$$

and a "pandemic loss rate" as the ratio between the stochastic pandemic losses and the value of the market portfolio. It defines which percentage of the market portfolio value gets lost through a pandemic

$$R_l = \frac{S_1}{W_0^m} \tag{5}$$

Hence, the rate of return of the market portfolio can be formulated as

$$r_m = r_{m*} - R_l \tag{6}$$

The first adjustment term in Equation (1) represents the market risk premium multiplied by the underwriting beta risk, and represents a markup for systematic risk. With the help of Equation (6), Equation (1) can be expressed via

$$\pi_{o,j}\, \beta_u = \pi_{o,j} \frac{cov\left(\frac{S_{1,j}}{\pi_{o,j}} - 1, r_{m*} - R_l\right)}{\sigma_{r_m}^2} = \frac{cov(S_{1,j}, r_{m*})}{\sigma_{r_m}^2} - \frac{cov(S_{1,j}, R_l)}{\sigma_{r_m}^2} \tag{7}$$

The last term in Equation (1) represents an adjustment for systematic skewness, i.e., the market skewness premium multiplied by the co-skewness of the insured risk with the market portfolio. The term $\pi_{o,j}\, \gamma_u$ can be rewritten as

$$\pi_{o,j}\, \gamma_u = \pi_{o,j} \frac{cov\left(\frac{S_{1,j}}{\pi_{o,j}} - 1, (r_m - \mu_m)^2\right)}{\tau_{r_m}^3} = \frac{cov\left(S_{1,j}, (r_m - \mu_m)^2\right)}{\tau_{r_m}^3} \tag{8}$$

$$= \frac{cov\left(S_{1,j}, (r_{m*} - R_l - (E(r_{m*}) - E(R_l))^2\right)}{\tau_{r_m}^3}$$

with

$$\tau_{r_m}^3 = E\left[\left(r_m - E(r_m)\right)^3\right] \tag{9}$$

With Equation (8), the premium formula (1) can be formulated as

$$\pi_{o,j} = \frac{1}{1+r_f}\left[E\left[S_{1,j}\right] - b_1\left(\frac{cov(S_{1,j}, r_{m*})}{\sigma_{r_m}^2} - \frac{cov(S_{1,j}, R_l)}{\sigma_{r_m}^2}\right) - b_2 \frac{cov\left(S_{1,j}, (r_{m*} - R_l - (E(r_{m*}) - E(R_l))^2\right)}{\tau_{r_m}^3}\right] \tag{10}$$

In the case of a positive skewness of the stochastic return of the market portfolio ($\tau_{r_m}^3 > 0$), b_2 is > 0.[3] Taking into account that b_1 is positive too, the premium adjustments solely depend on the sign of the three numerators in the square bracket of Equation (10). In particular, we have:

$\frac{cov(S_{1,j}, r_{m*})}{\sigma_{r_m}^2}$: The covariance term reflects the traditional CAPM beta factor[4]. If the (pandemic) loss tends to be above average in times of below-average capital market returns, this gives rise for a systematic risk premium charge.

$\frac{cov(S_{1,j}, R_l)}{\sigma_{r_m}^2}$: The second covariance term reflects the cumulative risk coming along with pandemic risks. If the (pandemic) loss tends to be above average when the pandemic loss rate is also above average, i.e., when the aggregate losses are above average compared to the present value of the market portfolio, then this requires a cumulative-risk-markup. Investors of the insurance company require a compensation for such cumulative risk that worsens their situations in pandemic-related "bad times".

$\frac{cov(S_{1,j}, (r_{m*} - R_l - (E(r_{m*}) - E(R_l))^2)}{\tau_{r_m}^3}$: One gets a positive skewness markup, if a positive skewness of capital market returns is lowered by insuring pandemic risks.[5] This can be the case if (pandemic) losses tend to be above average in situations in which the squared excess return of the market portfolio is below average. The latter can be even far below average for high pandemic loss rates R_l in otherwise very good capital market scenarios. Thus, high cumulative risks, as reflected by R_l, can exacerbate the skewness markup through its effect on the market portfolio. In such a situation, the owners of an insurance company suffer disutility from the pandemic risk-induced reduction of the investment return skewness. If they are to offer insurance contracts that bring about high losses in these bad skewness times, they require a markup that compensates them for this disutility.

To sum up, our analysis implies that insurers have to charge a price for pandemic insurance that is above the (risk-free discounted) expected loss, if the losses are negatively correlated with the return of the market portfolio, if losses occur at the same time and have a significant impact on the value of the market portfolio, and if they lower the otherwise positive skewness of the capital market returns.

<u>Reservation price of the demand side</u>

[3] Cf. Kraus and Litzenberger (1976), p. 1088.

[4] Cf. Fairley (1979).

[5] See Kraus and Litzenberger (1976) and Scott and Horvath (1980) who argue that individuals like positively skewed asset returns.

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

$$W_1 = A_1 - S_1 \tag{11}$$

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

$$W_1 = A_1 - \pi_0^{gross} \tag{12}$$

Hereby, $\pi_0^{gross} = (1+\lambda)\pi_o$, with π_o given by Equation (10). 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 that is in line with maximizing expected utility, given an exponential utility function, and considering the first three moments of W_1.[6]

$$\Phi(W_1) = E(W_1) - \frac{a}{2} \cdot \sigma_{W_1}^2 + \frac{a^2}{6} \cdot \tau_{W_1}^3 \tag{13}$$

$\sigma_{W_1}^2$ stands for the variance of the wealth position of the customer, and $\tau_{W_1}^3$ for its skewness. Moreover, the risk aversion parameter $a > 0$.

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.

For the case without insurance we get for the expected wealth, its variance and skewness

$$E\left(W_1^{w/o}\right) = E(A_1) - E(S_1) \tag{14}$$

$$\sigma_{W_1^{w/o}}^2 = \sigma_{A_1}^2 + \sigma_{S_1}^2 - 2\, cov(A_1, S_1) \tag{15}$$

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

$$\tau^3_{W_1^{w/o}} = \frac{E\left((A_1 - S_1)^3\right) - 3\,E(A_1 - S_1)\,\sigma^2_{A_1 - S_1} - (E(A_1 - S_1))^3}{\left[\sigma^2_{A_1} + \sigma^2_{S_1} - 2\,cov(A_1, S_1)\right]^{3/2}} \tag{16}$$

By setting r_f = 0 and substituting the risk adjustment terms in Equation (10) by R_{adj}, the first two central moments and the skewness of the wealth distribution with full coverage are given by

$$E\left(W_1^{with}\right) = E(A_1) - (1 + \lambda)\,(E[S_1] + R_{adj}) \tag{17}$$

$$\sigma^2_{W_1^{with}} = \sigma^2_{A_1} \tag{18}$$

$$\tau^3_{W_1^{with}} = \frac{E\left({A_1}^3\right) - 3\,E(A_1)\,\sigma^2_{A_1} - (E(A_1))^3}{\left[\sigma^2_{A_1}\right]^{3/2}} \tag{19}$$

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

$$\begin{aligned}\Phi\left(W_1^{with}\right) - \Phi\left(W_1^{w/o}\right) = &-\lambda\,E[S_1] - (1 + \lambda)R_{adj} \\ &+ \frac{a}{2}\left(\sigma^2_{S_1} - 2\,cov(A_1,\, S_1)\right) \\ &+ \frac{a^2}{6}\left(\tau^3_{W_1^{with}} - \tau^3_{W_1^{w/o}}\right) > 0\end{aligned} \tag{20}$$

Equation (20) provides an economic interpretation of the determinants for purchasing pandemic insurance, i.e. for insurability. By purchasing insurance, the policyholder gets rid of the pandemic risk contribution $\frac{a}{2}\,(\sigma^2_{S_1} - 2\,cov(A_1,\, S_1))$. The typical case is a negative $cov(A_1,\, S_1)$, i.e., the loss tends to be above average in states in which her 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 non-insurable 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 $\sigma^2_{S_1}$. Neglecting skewness issues in the third line of (20) for the moment, insurance purchasing becomes advantageous if the benefit through the lowered risk is not outweighed by the cost of insurance (above the expected loss). I.e., the risk adjustments in the insurance premium according to Equation (10) increased through the premium markup λ. Regarding the first two lines of Equation (20), for signing the insurance contract it is necessary the sum of the systematic risk charge ($-b_1 \frac{cov(S_{1,j}, r_{m*})}{\sigma^2_{r_m}}$), the cumulative risk charge ($b_1 \frac{cov(S_{1,j}, R_l)}{\sigma^2_{r_m}}$), and the skewness risk charge ($-b_2 \frac{cov(S_{1,j}, (r_{m*} - R_l - (E(r_{m*}) - E(R_l))^2)}{\tau^3_{r_m}}$) must not exceed the individually valued transferred pandemic risk ($\frac{a}{2}\,(\sigma^2_{S_1} - 2\,cov(A_1,\, S_1))$).

The third line in Equation (20) reflects the individually valued change in the skewness of the customer's cash flows when purchasing insurance. It can be expected that the third line is 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 her final wealth and increases her utility level. Therefore, considering skewness in the individual

In summary, the analysis of insurance demand implies that policyholders are willing to pay a higher price for the pandemic insurance if a pandemic risk also affects wealth and income components that are not directly hit by the pandemic disease. An example could be losses in revenues in other uninsured lines of business or pandemic-related higher tax payments. In addition, the policyholders' willingness to pay increases the more pandemic risks contribute to a lower positive skewness of final wealth if they remain uninsured.

The theoretical analysis above is based on a single individual and helps to elicit the parameters leading to insurability and non-insurability of pandemic risks. Yet, to estimate the market size for pandemic insurance it would be necessary to predict the purchasing decision for all individuals, taking their different wealth situation, risk attitudes, and decision-making criteria in general into account. To do this in a direct way is, in our view, not possible. In the following empirical part, we therefore go a different way to assess the market size for pandemic insurance. We rely on previous studies on the market of catastrophe insurance for which supply and demand functions were derived that implicitly map insurance customers' characteristics. We then calibrate those functions with pandemic risk data and can thus derive predictions on the pandemic insurance market.

IV. Empirical Assessment of the Market for Pandemic Risks

The key insight of the theoretical framework is that pandemic insurance supply and demand depend 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, we develop an assessment of the market for pandemic risk insurance using data on the severity of the economic impact of COVID-19 in the US as well as data on the pricing and volume of the US insurance market for natural catastrophes (hurricanes, wind, fires, earthquakes). Our approach is to estimate the model for the catastrophe insurance market and then use it to evaluate the market for a hypothetical insurance contract that is designed to alleviate the economic impact of the pandemic to individuals and small businesses whose activities are interrupted due to the pandemic.

Our analysis consists of three parts. We first propose a hypothetical insurance contract which would provide financial relief for the job loss and business interruption documented in Chetty et al. (2020a) and Alexander and Karger (2020). Then we derive a loss distribution for the hypothetical pandemic insurance contract using two sources of data. The severity of the economic losses of the pandemic is calibrated using the publicly available dataset on the economic impact of COVID-19 developed by Chetty et al. (2020b) and the Opportunity Insights Team. This dataset (further discussed below) contains granular high-frequency (daily) data on consumer spending, business revenues, employment rates and other key economic indicators that can be linked to the COVID-19 infection rates at the county level per 100,000 inhabitants. 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 socio-economic, environmental, and ecological factors. Given a high degree of uncertainty and complexity about the frequency of these diseases, we calibrate the loss distribution for a range of plausible frequencies.

In the second part, we assess the price and the volume of insurance for the hypothetical contract. To do so, we treat it as an insurance contract with catastrophic exposures and calibrate its price and supply using the existing market of homeowners' insurance with catastrophic loss exposures in the US. We first estimate the model that explains how the price of insurance with catastrophic exposures depends on the characteristics of the loss distribution (volatility of losses and fatness of the tail) and the correlation of insurers' stock returns with the market portfolio. Then – given the loss distribution of the hypothetical contract calibrated in the previous step, and the actual correlation of the insurers' stock returns with the market index during the pandemic in 2020 – we use the estimated model to calculate the price of the hypothetical insurance contract and the elasticity of insurance supply.

Turning to insurance demand, our calibration of the demand function builds on the literature that estimates the individual demand for catastrophic insurance and the income elasticity of demand. Browne and Hoyt (2000) analyze the financial performance of the US National Flood Insurance Program to estimate how flood insurance demand depends on the price of coverage and the income of perspective policyholders. Millo (2016) develops an aggregate analysis of the non-life insurance market and concludes that insurance is a normal good, i.e. with elasticity of demand less than one.

In the third part, we evaluate the insurance market equilibrium for the pandemic-risk insurance contract and discuss how it compares to the market of natural catastrophe insurance.

V. Pandemic Insurance Contract

We consider a hypothetical contract designed to compensate the loss of income to individuals employed in sectors that require in-person physical interaction and thereby carry a risk of COVID-19 infection, e.g. beauty and wellness services, entertainment, food services, transportation, hotels.

Our choice of a hypothetical contract is motivated by the analysis of the economic impact of COVID-19 documented in Chetty et al. (2020a) and Alexander and Karger (2020). They identify the mechanisms through which COVID-19 affected employment and small business operations. Chetty et al. (2020a) find that high-income individuals sharply reduced their spending in geographic areas with a high infection rate and in sectors with in-person interaction. The reduction translated to the decrease in revenues in small businesses that cater high-income households in person. Consequently, these businesses laid off many of their workers who are primarily low-wage workers. These results corroborate with 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 re-openings of the economies have a small impact on spending and employment, confirming that it is the infection rate which collapses the demand for in-person services.

These analyses suggest that the direct financial support to individuals and small businesses is best suited to mitigate the economic hardship during the pandemic. In line with this conclusion, we consider the following hypothetical insurance contract: In exchange for an up-front premium P, the contract stipulates a contingent constant monthly payment C for T months, triggered by the declaration of the epidemic/pandemic by a national or a supranational authority, or a shut-down mandated by the government. The probability of the pandemic is q. Then the payment of the contract to a policyholder is CT with expectation qCT. In the baseline calibration we set T=12 and C=$2000, i.e., the contract provides a compensation for the loss of basic income of $2000 for the period of 12 months. We also consider two less generous alternatives, C=$1500 and C=$1000. As we discuss below, a similar contract could be offered to small businesses providing in-person services in which case the insurance would cover the loss of revenue during the pandemic.

VI. Data

Our data is obtained from four sources. The loss distribution of the hypothetical insurance contract is calibrated using the data on the economic impact of COVID-19 developed by Chetty et al. (2020b) and the Opportunities Insights Team. Information on the homeowners' insurance market is based on the statutory regulatory reporting of the US insurers and is obtained from the Standard and Poor's Market Intelligence Platform. The estimates of the frequency and severity of the natural catastrophes across geographic areas in the US are based on Froot and

O'Connell (2008). The market data on insurers' stock returns, the stock market indices and interest rates are collected from Bloomberg.

Data on the economic impact of COVID-19

Chetty et al. (2020b) and the Opportunities Insights Team (OIT) have developed a publicly accessible platform that measures spending, employment, small business activity and others at a high-frequency granular level using anonymised data from private companies in the US. The data time series mostly start in 2018 or 2019, depending on the series, and are reported on a daily basis at a ZIP code level. In our analysis we use the following data: The data on consumer spending is based on Affinity Solutions Inc data which aggregates consumer credit and debit card spending information. In addition, cash transactions activity is measured using data from CoinOut. The data on employment and earnings originates from Paychex and Intuit, worker-level employment and earnings from Earnin and time-sheet data from Kronos. The data on small business revenues is aggregated from Womply. The data on job postings (available from 2007 on) is obtained from Burning Glass Technologies.

Combined with the infection rates reported by the Center for Disease Control in the US, 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.

Homeowners insurance market data

We estimate the model of insurance supply with catastrophic exposures using the data on homeowners and farmowners insurance in the United States. This line of business is well-suited for our analysis of catastrophe risk supply for several reasons. The homeowners insurance coverage includes physical damage to the property from natural hazards, and thus is subject to catastrophic risks from natural hazards in the hazard-prone zones. It is a large segment of the personal insurance market serving individuals and households.

In our analysis we use the annual regulatory statutory filings of a sample of publicly traded property-casualty insurers in the US. Table 1A in the Appendix presents the list of insurance groups included in the sample. We obtain information on the direct premiums written at the state-company-year level. The state level granularity is important as states vary in their exposure to natural catastrophes, i.e. a hurricane is more likely to occur in Florida than in California.

Insurers do not report insurance prices in their statutory filings but the price markup above the paid loss can be calculated from the regulatory filings. Consistent with previous literature (Cummins and Danzon, 1997; Sommer, 1996), to calculate insurance price markups we collect

the information on actual paid losses and other expenses reported in Schedule P. For each accident year, Schedule P provides the information on paid losses for the subsequent 10 years. During these 10 years, the liabilities are practically exhausted. Thus, the discounted sum of these payments represents the total paid losses. Dividing the direct premiums written by the total paid loss provides a markup, i.e. the premium above the paid loss for each insured dollar of exposure. To be able to observe the complete series of payments during the 10 years beginning with the accident year, we restrict our analysis to 2000-2010.

Data on the frequency and severity of natural catastrophes

We use the estimated loss distributions for natural catastrophes across the geographic areas in the US as reported in Froot and O'Connell (2008). They estimate the distributions of catastrophe frequency and severity using data from Property Claims Services (PCS) which has catalogued all catastrophe losses on an industry-wide basis since 1949 by type and US region. Tables 2 and 3 in Froot and O'Connell (2008) report the frequency using the Poisson parameters and the severity fitted in with Lognormal or Pareto distributions. We use these estimates to calculate the volatility of losses and the fatness of the tail of the loss distribution for each geographic area.

Market data

We obtain the data on the insurers' stock prices, the S&P 500 index, and US ten-year constant maturity note rates for the period 2000-2010. These data are used in the estimation of the catastrophic insurance supply model. In addition, we use the S&P property-casualty insurers index in 2020 to assess the correlation between the insurers' stock performance and the market portfolio during the pandemic. This estimate is used in the calibration of the price of a hypothetical insurance contract.

VII. Supply of pandemic insurance

Building on our theoretical framework, the supply of pandemic insurance (or any catastrophic insurance) depends on the characteristics of the loss distribution and the co-movement of the insurers returns with the financial market. The characteristics of the loss distribution which are particularly relevant for catastrophic risk exposures are the volatility of losses and the fatness of the tail of the loss distribution. The dependence of insurance supply on the co-movement of insurers' returns with the market portfolio summarizes the insurers' underwriting, investment and capital budgeting strategy. Even when the losses are uncorrelated with the financial market, which is arguably the case for insured natural catastrophes (or at least, those that have occurred so far), insurers' pro-cyclical capital budgeting and investment strategy can translate into the sensitivity of insurance prices to financial market downturns (Koijen and Yogo, 2017).

The supply function is

$$\ln CT = e_p^s \ln P \tag{21}$$

where e_p^s is the price elasticity of supply of pandemic insurance. We assume that the price elasticity of pandemic insurance supply depends on the characteristics of the loss distribution and the systematic exposure to the financial market performance.

In the rest of the section we proceed in two steps. First, we estimate the model of pricing of catastrophe insurance. Then, we calibrate the loss distribution of the hypothetical insurance contract and apply the model to evaluate the price at which insurers would be willing to provide pandemic risk coverage.

<u>Pricing of catastrophe insurance</u>

<u>Econometric Specification</u>

To calibrate the elasticity e_p^s for the pandemic-risk insurance contract, we estimate how the pricing of catastrophic insurance depends on the parameters of the loss distribution and the co-movement of insurers' returns with the financial market. As discussed in the Data section, we estimate the model using the annual regulatory reporting of the US insurance companies in 2000 - 2010 and consider the homeowners and farmowners lines of business. Because insurance prices are not observed directly, our measure of price is a markup charged above the paid losses and other expenses In the data, the markup can be calculated by dividing the direct premiums written in year t in a particular line of business by the actual paid losses in the accident year t and the following nine years t+1,..,t+9 as reported in Schedule P. For discounting we use the US Treasury yield curve (Cummins and Danzon, 1997; Sommer, 1996).

The regression to be estimated is

$$(1+\lambda)_{it} = \beta_{vol} \ln\left(\sigma_{vol}^2\right)_{it} + \beta_{FT} \ln(\sigma_{FT}^2)_{it} + \beta_M \ln(\sigma_M^2)_{it} + \gamma_i + \theta_t + \varepsilon \tag{22}$$

where $(1+\lambda)_{it}$ is the markup of insurer i in year t, $\left(\sigma_{vol}^2\right)_{it}$and $(\sigma_{FT}^2)_{it}$ are the measures the volatility and the fatness of the tail of the loss distribution of insurer i in year t, $(\sigma_M^2)_{it}$ measures the correlation between insurer's i stock market performance and the market portfolio in year t, γ_i and θ_t are insurer and year fixed effects and ε is the error term to account for unobserved factors driving the price markup. β_{vol}, β_{FT} and β_M are parameters to be estimated.

In our regression specification, the volatility and fat tail measures refer to the premium components $b_1 \frac{cov(S_{1,j},R_l)}{\sigma^2_{r_m}}$ and $b_2 \frac{cov(S_{1,j},(r_{m*}-R_l-(E(r_{m*})-E(R_l))^2)}{\tau^3_{r_m}}$. in Equation (10). $(\sigma^2_M)_{it}$ is the correlation between insurer's i stock market performance and the market portfolio in year t, and, because stock market performance is partly driven by the insurer's loss distribution, refers to the premium component $b_1 \frac{cov(S_{1,j},r_{m*})}{\sigma^2_{r_m}}$ in Equation (10).

The characteristics of the loss distributions for catastrophic exposures can be estimated from the reported economic losses from natural hazards in the US. In our analysis, we rely on the distributions for perils and geographic classifications estimated by Froot and O'Connell (2008). Their analysis considers exposures to earthquake, fire, hurricane, and windstorm which tend to result in higher losses compared to other natural perils. The loss distributions for each of these exposures are calibrated for five US regions, Northeast, Southeast, Texas, Midwest and California, and four quarters per year. Froot and O'Connell's classification of perils and geographics allows them to estimate around 30 loss distributions. Given that we are limited to the yearly granularity of the loss data in Schedule P, we aggregate the loss distribution estimates to yearly frequency. In addition, we aggregate the loss distributions across different types of perils in the region. These modifications lead to the total of 5 distributions which are reported in Table 1.[7]

Schedule P data reports firm-level 10-year loss development for a given line of business in all states. Therefore, in Equation (22) the measures $\left(\sigma^2_{vol}\right)_{it}$ and $(\sigma^2_{FT})_{it}$ correspond to the aggregate distribution of insurer's exposure across the geographic regions with active business in homeowners and farmowners lines in a given year. To construct the aggregate distribution of exposures, we weight the loss distribution in region j by α_{itj} which is the share of direct premiums written (DPW) in homeowners and farmowners insurance in region j for each insurer-year it; that is,

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

To the extent that the shares 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 $\left(\sigma^2_{vol}\right)_{it}$ and $(\sigma^2_{FT})_{it}$.

The co-movement between an insurer's i stock performance in year t and the market portfolio in year t, $(\sigma^2_M)_{it}$ is estimated using a sample of insurers' stock returns and the S&P 500 index

[7] An advantage of our approach to build on Froot and O'Connell (2008) estimates is its simplicity though it bounds us to aggregate the loss distributions to regions. An alternative approach is to model the exposure to catastrophic losses at the state level using, for example, the SHELDUS™ hazard data set for the U.S.

in 2000-2010. We employ a standard two-factor CAPM specification following the methodology in Hartley et al. (2016). We estimate the following regression:

$$R_{it} = a + b_{it}R_{m,t} + c_{it}R_{10,t} + \eta_{it} \tag{23}$$

where R_{it} is the return (including dividends) on stock *i* in week *t*, $R_{m,t}$ 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 (22), $(\sigma_M^2)_{it} = b_{it}$.

Empirical Results

The summary of the estimation of insurers' betas results of the two-factor CAPM model are presented in Table 2. The firm-year estimates of the two-factor model are reported in Table A2 in the Appendix. In the overall sample, the mean and the median betas in Table 2 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 2000-2010, suggesting that the property-casualty insurance stocks become more synchronized with the market over time, which also reflects the influence of the 2008/2009 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 is not significant (see Table A2), consistent with the short-term nature of non-life insurance liabilities.

The estimation of the markup regression (22) is presented in Table 3 and Table 4. The summary statistics of the variables in regression (22) are presented in Appendix Table 3A. Table 3 panel A reports the summary statistics of the volatility, expected shortfall and the market betas in the sample. As our construction of the insurers' catastrophe loss exposures relies on loss distributions which are aggregated to large geographical regions, it reduces the variability within the regions. As a consequence, our estimates of volatility and the expected shortfall are highly correlated, as reported in Table 3 panel B. As a remedy to the collinearity issue we have estimated the markup model using only the expected shortfall to characterise the loss distribution.

The estimation results are presented in Table 4. The coefficient of the expected shortfall is positive and significant. It indicates that a 10% increase in expected shortfall leads to 2.2% increase in the markup. The coefficient of the insurer's market beta is insignificant which is consistent with the low-level economic impact of the insured natural disasters on the US financial market. The regression in Table 4 also includes (unreported) firm and year fixed effects. The insurer fixed effect 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, i.e. higher tail risk.

Our estimation procedure of catastrophe insurance pricing can be refined in two dimensions. First, as mentioned above, it is possible to use the state level granularity of the losses from natural hazards as reported in SHELDUS™. That would permit to have a richer set of loss distributions (50 instead of 5) for catastrophic risk exposures. Second, the analysis can be extended to the full set of 10 business lines with catastrophic exposures listed in footnote 2. These extensions would permit to estimate a richer model and enable us to use a more comprehensive set of characteristics of the loss distributions.

Calibration of the pandemic loss distribution and the pandemic insurance markup

The insurance payment of the hypothetical insurance contract is triggered by the loss of employment caused by the reduction of in-person business activity due to the risk of infection. To calibrate the loss distribution, we need to assess the severity of losses and the frequency of the pandemic. To calibrate the severity of the pandemic loss distribution, we use the data reported in Chetty et al. (2020b). To calibrate frequency, we refer to the recent literature in epidemiology that documents the rise of emerging infections' diseases in the recent decades (Jones et al., 2008; Ross et al., 2015).

The data collected by the Opportunities Insights Team reports the unemployment claims, small business closures, small business revenues and the contraction of consumer spending as a function of the infection rate per county in the US. These data allow to estimate the impact of the new cases on the indicators of the economic activity. 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 reveal 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 of the infection rates from 0.0654 to 49.2 per 100'000 inhabitants that reflect 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%.The growth of the infection rate also reduces the revenues of small businesses and the number of open small businesses, as reported in columns [5] and [6].

In 2020, the strongest contraction of employment and small businesses economic activity occurred during the first wave of the infection in February – March 2020. Table 5 panels B to C report the regression results for the key economic indicators relevant for the hypothetical

insurance contract, new unemployment claims and small business activity during the three quarters in 2020. Comparing the regression coefficients between the first and the other quarters emphasizes the importance of the initial shock of the infection outbreak. Once the businesses are closed and workers are let go, the subdued economic activity persists through the following quarters.

The estimation results of Table 5 allow 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 growing infection rates reported in Table 5 at the county level. In total, our sample consists of 3141 counties in the US. We weight counties by their population. The result is the empirical distribution of predicted new unemployment claims across the US counties. We use this empirical distribution to assess the standard deviation and the expected shortfall of the loss distribution for the hypothetical insurance contract.

Given the baseline assumptions that the contract provides the coverage for the basis income of $2,000 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 US, we can estimate the total new claims and the claim costs as a function of the infection rate. Figure 1 depicts the distribution of losses and Table 6 reports the statistical characteristics of the loss distribution. The losses of the hypothetical contract are reported on the aggregate industry basis. That is, the estimated expected shortfall of $4,6 trillion corresponds to the aggregate expected shortfall for the insurance industry if the small business workers were fired because of the pandemic, but hold the hypothetical unemployment insurance contract. We also report the estimates for two alternative less generous contract pay-outs of $1000 and $1500 per month.

Turning to the frequency of the pandemic, Jones et al. (2008) report a growing frequency of emerging infection diseases that, like COVID-19, originate in wildlife and have recently entered human populations for the first time. The most prominent examples prior to 2020 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 the emerging diseases. Considering the evolving nature of the risk, we calibrate the model for a range of plausible frequencies. On the conservative side, in terms of its global impact COVID-19 can be compared to the Spanish Flu outbreak in 1917 which would suggest a 1-in-100 years frequency. We also model the loss distribution with 1-in-50, 1-in-25 and 1-in-10 years frequencies.

To put our findings in perspective, it is illustrative to compare the expected shortfall characteristics of the pandemic insurance contract to the expected shortfall that a typical insurer bears in underwriting homeowners insurance with catastrophe loss exposures. To do

so, we need to allocate the estimated aggregate industry losses of the pandemic insurance contract among the insurers. To make a realistic estimate, we weight the aggregate loss by the insurers' average market share in the homeowners' insurance. The results are illustrated in Figure 2. The red segment in Figure 2 depicts the range of expected shortfall and the corresponding markup for monthly pay-out amounts of $2000 for an insurer covering between 3% and 15% of this hypothetical market, obtained using the estimates of (22) and the characteristics of the pandemic loss distribution. The cloud of blue dots are the values of the markups and the expected shortfalls of homeowners' insurance for insurers in the sample. Figure 2 shows that the expected shortfall of the pandemic loss distribution is higher than the typical shortfall of homeowners insurance. Thus, the markup that the insurers would require to provide coverage for pandemic losses will also be higher. For an insurer with a market share of 15% in this hypothetical market that would correspond to the top 12.1% of the markup in the loss distribution of homeowners losses.

In sum, our results suggest that there is some scope for the private market for pandemic loss coverage. An important caveat is that our estimation is based on 1-in-100 frequency while, as we discussed above, the occurrence probability of pandemics is growing. In addition, our estimation is restricted to one line of business with catastrophe loss exposure. Estimating the catastrophe insurance supply using more comprehensive data about the natural catastrophes loss distributions and the markup in other business lines exposed to catastrophe can be used to derive more robust conclusions about the scope for private insurance supply. These extensions can be implemented by using the SHELTUS data and by including other business lines with catastrophe loss exposure.

Calibration of the equilibrium pandemic insurance coverage

The estimated markup of the catastrophe risk coverage λ_{COVID} can be used to calibrate the supply of insurance,

$$\ln CT = \frac{1}{1+\lambda_{COVID}} \ln(P).$$

The supply function states that a 1% increase of insurance price will lead to <1% increase in insurance supply, and the wedge is higher the higher is the markup λ_{COVID}.

The demand for insurance is increasing in the premium and decreasing in policyholders' income. The demand function is

$$\ln CT = e_p \ln P + e_w \ln w$$

where e_p is the price elasticity of demand, w is the policyholder's income and e_w is the income elasticity of demand, with $e_p < 0$ and $e_w > 0$. The demand function can be calibrated by using the estimates of the demand elasticities with respect to price and income from the insurance

literature. Browne and Hoyt (2000) analyse the flood insurance market in the US 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 in the policies per capita model and -0.997 in the insurance in force per capita model. The income elasticity of demand is estimated at 1.506 in the insurance in force model and 1.400 in the policies per capita model. These estimates indicate that the demand for catastrophe insurance is quite sensitive to income. Millo (2016) estimates the income elasticity of demand on the aggregate insurance market level and finds that the elasticity is around one.

The calibrated demand and supply functions can be used to assess the size of the pandemic insurance market. Then one can evaluate to which extent the private pandemic insurance can supplement the social insurance and to compare the coverage to the actual support from the government programs.

VIII. Implications for the Design of the Pandemic Insurance Market

Our findings suggest that there could be limited private market for the pandemic insurance. Based on 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 ability to transfer risks to the financial market and the role of the government. Several such proposals are being discussed between the regulators and the insurance industry.

OECD (2020) also reviews some of the recent proposals though also notes that these proposals are still evolving. The European Insurance and Occupational Pensions Authority (EIOPA) published an issues paper discussing the issues and options for establishing a EU-wide insurance solution for addressing pandemic-related business interruption losses ("shared resilience solution"). In France, the French Minister of Economy and Finances established a working group tasked to develop a framework for providing insurance for extreme events like COVID-19 pandemic. The French insurance industry association has also published a proposal to provide coverage for business interruption losses that result from a reduction in economic activity due to extreme events (not restricted to pandemics). In Germany, the German insurance association suggested a similar arrangement where the state-funded fund would be used to pay the losses in case of a WHO-declared pandemic. In the United Kingdom, a proposal is to establish Pandemic Re which would create a government-backed reinsurance pool. In the United States, a proposal is to establish a federal pandemic risk reinsurance programme, Pandemic Risk Insurance Act of 2020 (PRIA). The programme is designed in a similar way as the Terrorism Risk Insurance Program. It would provide a federal backstop for business interruption and event cancellation losses incurred by participating insurers because of a "covered public health emergency."

Our analysis can be extended to analyse the merits of these proposals. Most of these proposals suggest that a publicly managed pool is established to provide the backstop for the insurance industry losses. Effectively, these arrangements imply the reduction of the expected shortfall for the insurers offering pandemic insurance. Our model can be used to evaluate the generosity of the support that would be required to achieve the reasonable market coverage and the share of the cost that need to be paid by the public.

IX. Concluding Remarks

We analyse the scope for the private insurance market for the pandemic risks. Considering pandemic as a catastrophic risk, we argue that the supply and the demand of insurance depends on the tail risks of the loss distribution. Then we calibrate the supply of a hypothetical insurance contract by the insurance industry based on the data reported in Chetty et al. (2020b). We show that indeed the markup that would be charged by insurers for this contract would be higher than the markup for coverage of natural catastrophe risks. We conclude that the private pandemic insurance market has limited scope.

Our analysis can be extended in several directions. We have discussed that the current estimation relies on aggregated loss distributions at the region level comprising several US states, and the analysis can be done on more granular state level. In addition, the estimation of catastrophe risk coverage can also include other lines of business. These extensions will provide more comprehensive evaluation of catastrophe insurance supply and improve the robustness of our findings. Further, our analysis can be extended to evaluate the size of the risk transfer support (either through reinsurance or other mechanism) that is required to bring the insurance prices in line with prices for other catastrophic risks.

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Table 1: Frequency and Severity distributions by type, per region

This table presents frequency and severity distributions of CAT risks present in different regions. The table is based on frequency and severity distribution parameters presented by Froot and O'Connell (2008), in Tables 2 and 3; In line with their argument we have picked up the Lognormal severity distribution. Frequency is presented by the Poisson parameter λ, Pois(λ) and severity by the Lognormal distribution with parameters μ and σ, LN(μ , σ). We assume that the distributions are independent and run a simulation to estimate the standard deviation and expected shortfall at 1% for each region measured in bn USD, presented in the last two rows.

Type		CA	NE	SE	MW	TX
Earthquake	Frequency	Pois (0.216)				
	Severity	LN (-2.1; 1.964)				
Fire	Frequency	Pois(0.5)	Pois (0.124)	Pois (0.124)	Pois (0.124)	Pois (0.124)
	Severity	LN (-2,35; 1.196)	LN (-2,35; 1.196)	LN (-2,35; 1.196)	LN (-2,35; 1.196)	LN (-2,35; 1.196)
Hurricane	Frequency		Pois(0.3491)	Pois (0.5431)		Pois (0.3491)
	Severity		LN (-1.454;1.454)	LN (-1.233;1.61)		LN (-1.454;1.454)
Winter storm	Frequency		Pois (0.76)			
	Severity		LN (-2.44; 1.166)			
Windstorm	Frequency	Pois (0.4341)	Pois (0.37)	Pois (1.457)	Pois (2.131)	Pois (1.913)
	Severity	LN (-3.039; 0.859)	LN (-3.039; 0.859)	LN (-3.039; 0.859)	LN (-3.039; 0.859)	LN (-3.039; 0.859)
Overall risk	**SD**	**3.598**	**1.271**	**3.282**	**0.436**	**1.77**
	$ES_{1\%}$	**17.038**	**9.345**	**23.218**	**3.168**	**13.248**

Table 2: Estimated market betas for P&C insurers for each year 2000-2010

This table presents summary statistics of the estimated market betas for insurers in our sample. Market betas are estimated for each insurer for each year based on daily return data, we use the US ten-year constant maturity note yield to control for interest rate and the S&P 500 Index as a proxy for the market portfolio. 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, the market beta in a given year is estimated only if the stock was traded for a minimum of 200 days.

Time Period	Sample Size	Mean	Median	St. Dev	Min	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

Table 3: Summary statistics for Variables influencing the value of the markup.

Panel A of this table presents summary statistics of the variables that we use to estimate the markup regression. Values of volatility and expected shortfall (at 1 %) are calculated based on regional risk distributions presented in Table 2, weighted by the direct premium written by the firm in each region divided by the total of direct premiums written in the region by all insurers, for relevant aka. CAT affected line of businesses; measured in billion USD. Markups are calculated by dividing the discounted total payouts over the ten years following the policy writing year, with the net underwriting premium. We use the US Treasury Yield curve, averaged over December of each year, for discounting. Panel B presents the correlation matrix of the independent variables.

Panel A: Sample statistics of variables under consideration

	Sample Size	Mean	Median	St. Dev	Min	Max
Markup	1058	22.986	2.353	510.209	0.027	16597.46
SD of loss dist.	1058	0.005	0.001	0.019	0.000	0.214
$ES_{1\%}$ of loss dist	1058	0.034	0.009	0.110	0.000	1.274
Market Beta	1058	0.872	0.902	0.503	-1.457	3.438

Panel B: Matrix of correlations

Variables	(1)	(2)	(3)
(1) SD	1		
(2) ES1% of loss dist	0.998	1	
(3) Beta	0.051	0.057	1

Table 4: Markup dependency on the loss distribution characteristics and market correlation.

This table presents estimates of the percentage change in the markup value, given percentage changes in the expected shortfall of the loss distribution, at 1% significance level, and percentage changes in correlation to the market portfolio. Firm and year fixed effects are not reported but have been controlled for. Year fixed effects are found significant at 1% in 2002 and 2003 and at 5% in 2008 and 2010. Firm fixed effects are mostly significant. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels.

	Ln (Markup)
Ln ($ES_{1\%}$)	0.2200***
	-0.0428
Ln (Beta)	-0.0127
	-0.0319
Constant	1.2682***
	-0.2512
R^2	0.83
N	1,058

Table 5: Economic indicators dependency on COVID-19 new cases rate per 100`000 people

This table presents estimates of changes in [1] Count of initial unemployment insurance claims weekly, given the new Covid-19 infection cases per 100'000 people, weekly. Estimates of changes in [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 to $60,000); [4] Seasonally adjusted credit/debit card spending relative to January 4-31 2020 in all merchant category codes (MCC), 7 day moving average; [5] Percent change in number of small businesses open calculated as a seven-day moving average seasonally adjusted and indexed to January 4-31 2020; [6] Percent change in net revenue for small businesses, calculated as a seven-day moving average, seasonally adjusted, and indexed to January 4-31 2020; given the new Covid-19 infection cases per 100'000 people, seven day moving average. Panel A reports the estimates of the linear regression for the whole sample, which comprises data from February 01, 2020 till October 31, 2020 for 3'143 US counties. Panel B reports estimates for the number of initial unemployment claims at sub-period level, roughly quarterly excl. January 2020. Similarly, Panels C and D report the sub-period estimates for the percent change in the number of small businesses open and the percent change in the net revenues for small businesses. In Panel B-D, estimates for the three first sub-periods together have been presented, these differ from the corresponding estimates in Panel A which also include data for October 2020. County fixed effects have been controlled for and are found significant, although they are not reported. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels.

Panel A:

	[1]	[2]	[3]	[4]	[5]	[6]
Covid-19 New Case Rate daily		-0.0031***	-0.0012***	0.0004***	-0.0030***	-0.0028***
		(0.0000)	(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	0.35	0.29	0.34
N	50,164	119,582	140,067	439,788	124,624	124,624

Panel B: Number of initial unemployment insurance claims weekly, given Covid-19 new cases rate

	[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: Percent change in number of small businesses open, given Covid-19 new cases rate

	[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: Percent change in net revenue for small businesses, given Covid-19 new cases rate

	[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

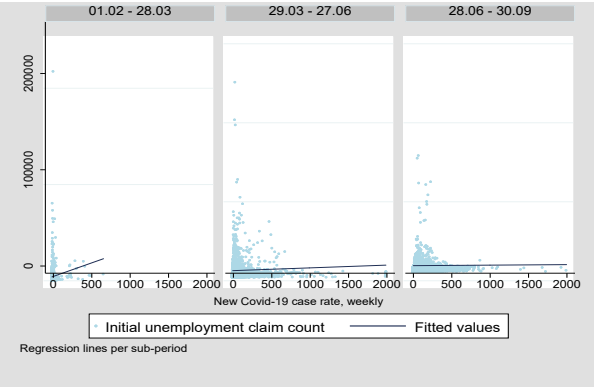

Figure 1: Number of new unemployment insurance claims as a function of the new Covid-19 weekly case rate, reported per quarter.

This figure plots the fitted regressions lines of the initial unemployment claim count, given the Covid-19 new case rate, measured weekly. The timeline is divided in three sup-periods. The fitted line represents an average, not displaying county fixed effects.

Table 6: Characteristics of loss of the hypothetical contract given the Covid-19 pandemic loss and insurance market correlation

The Covid-19 event loss of the contract is calculated by multiplying the total number of initial unemployment claims resulted during the pandemic with the lump sum of 2000 USD for 12 months. Based on the regression analysis of the relationship between new infection cases and unemployment claims, we limit the total number of initial unemployment claims to those fitted for the period between 01.02.20 – 30.06.20, using the two first regressions in Table 5, Panel B. We refer to epidemiologic literature (see Jones et al., 2008; Ross et al., 2015) that suggest a frequency of 0.01 for pandemics. For estimating the severity distribution of an event of the scale of Covid-19 Pandemic, we consider each county in the US as a homogenous unit and fit the distribution of 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. Note that because we exclude negative predicted number of claims, the overall value is slightly overstated. Given the distribution of the number of UC we can calculate the loss distribution of our contact. Figures for contracts with a payout of 1500USD and 1000USD have been provided for comparison. The market beta has been estimated in the same fashion

as firm betas in Table 1, by using S5PROP Index as proxy for the P&C Insurance market, the time period considered is 01.01.2020 – 13.11.2020.

Contract Payout	SD	$ES_{1\%}$	Market Beta
2000 USD	**1.77 trillion USD**	**4.6 trillion USD**	**.992**
1500 USD	**1.32 trillion USD**	**3.5 trillion USD**	**.992**
1000 USD	**0.88 trillion USD**	**2.3 trillion USD**	**.992**

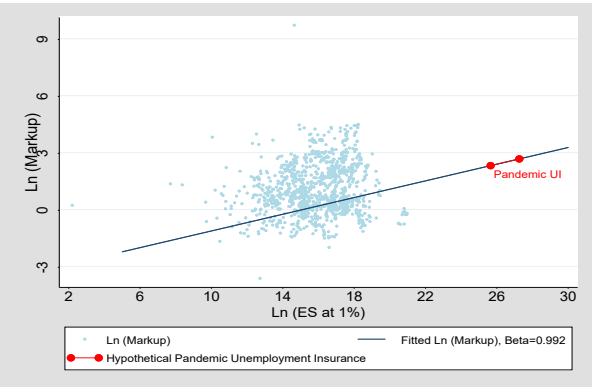

Figure 2: Markup as a function of Expected shortfall, log -log regression.

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 market beta to 0.992. The fitted line represents an average, not displaying year and firm fixed effects. The red segment represents the Hypothetical Pandemic Unemployment Insurance contract burden for firms with a market share of 3-15%. We have based our estimation of the market share on the average market share of firms in the Home- and Farmowners line of business, on the state level, which is approximately 3% with a standard deviation of 6%. We focus on the upper tail of the confidence interval to consider the upper limit of exposure to this contract's loss for a firm, given a high market concentration.

Table 7: Size of loss and estimated markup for our Hypothetical contract with payout 2000USD, on firm level, given market share assumptions.

This table presents the expected shortfall at 1% and estimated markup for firms covering a market share of 3, 9 and 15% of our hypothetical pandemic unemployment insurance market. The markup has been estimated assuming a beta fixed at the estimated beta of the P&C insurance market to overall market portfolio in 2020 as detailed in Table 6, 0.992. 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.

Market Share	$ES_{1\%}$	Est Markup (1+ λ)	Quantile
15 %	**690 billion USD**	**14.98**	**12.1%**
9 %	**414 billion USD**	**13.38**	**13.99%**
3 %	**138 billion USD**	**10.51**	**18.15%**

Appendix

Table 1A: List of 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)
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)
42	Biglari Holdings Inc. (SNL P&C Group)

Table 2A: Estimated market betas for P&C insurers yearly

This table presents estimates of market beta for each insurer in our sample, yearly. Betas have been estimated based on daily returns over one 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 ten-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.

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

Table 2A: Estimated market betas for P&C insurers, yearly – continued

P & C Insurer	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
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
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

Table 3A: Summery statistics on yearly basis of the variables entering the markup regression

This table presents summary statistics on yearly basis of the variables entering the regression (22). Note that we have also presented descriptives of the standard deviation of the loss distribution although we exclude it from the final regression due to multicollinearity with the $ES_{1\%}$, given the limited number of loss distribution as extracted from Froot and O'Connell (2008).

Year		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Sample size		105.00	99.00	98.00	101.00	96.00	98.00	99.00	95.00	92.00	91.00	83.00
Markup	Mean	5.90	6.13	0.00	9.60	7.45	6.98	8.10	8.77	8.07	7.78	7.12
	Median	2.04	2.09	0.00	3.09	2.53	2.42	3.17	2.57	2.19	2.22	2.66
	Std. Dev.	10.03	10.19	0.00	16.56	12.46	10.42	12.68	16.20	13.88	15.27	13.50
	min	0.24	0.27	0.00	0.25	0.31	0.24	0.23	0.23	0.30	0.29	0.36
	max	71.10	69.87	0.00	87.11	90.38	60.68	75.14	87.72	74.52	86.05	86.24
SD	Mean	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Std. Dev.	0.02	0.02	0.00	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	max	0.21	0.21	0.00	0.19	0.19	0.19	0.18	0.17	0.15	0.14	0.13
ES at 1%	Mean	0.03	0.03	0.00	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.03
	Median	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01
	Std. Dev.	0.13	0.13	0.00	0.12	0.11	0.11	0.11	0.10	0.10	0.09	0.09
	min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	max	1.27	1.25	0.00	1.12	1.09	1.08	1.02	0.97	0.87	0.80	0.78
Beta	Mean	0.58	0.62	0.00	0.75	0.81	0.81	0.85	0.95	1.21	1.46	1.05
	Median	0.56	0.68	0.00	0.83	0.86	0.94	0.86	1.04	1.27	1.28	1.02
	Std. Dev.	0.36	0.26	0.00	0.49	0.38	0.45	0.31	0.33	0.43	0.77	0.40
	min	-0.43	0.04	0.00	-0.20	0.16	-0.34	0.18	-0.23	0.01	0.02	-0.11
	max	1.17	1.54	0.00	1.51	1.57	1.59	1.42	1.55	2.28	3.44	1.80