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A Re-examination of the U.S. Insurance Market's Capacity to Pay Catastrophe Losses

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Abstract. Cummins, Doherty, and Lo (2002) present a theoretical and empirical analysis of the capacity of the property liability insurance industry in the U.S. to finance catastrophic losses. In their theoretical analysis, they show that a sufficient condition for capacity maximization is for all insurers to hold a net of reinsurance underwriting portfolio that is perfectly correlated with aggregate industry losses. Estimating capacity from insurers' financial statement data, they find that the U.S. insurance industry could adequately fund a $100 billion event in 1997. As a matter of comparison, Hurricane Katrina in 2005 cost the insurance industry $40 to $55 billion (2005 dollars). Our main objective is to update the study of Cummins et al (2002) with new data available up to the end of 2020. We verify how the insurance market's capacity has evolved over recent years. We show that the U.S. insurance industry's capacity to pay catastrophe losses is higher in 2020 than it was in 1997. Insurers could pay 98% of a $200 billion loss in 2020 in comparison to 81% in 1997.

Keywords: Catastrophe loss, U.S. insurance industry, industry capacity, reinsurance, climate finance, climate risk.

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Introduction

Cummins, Doherty, and Lo (2002) present a theoretical and empirical analysis of the capacity of the property liability insurance industry in the U.S. to finance catastrophic losses. In their theoretical analysis, they show that a sufficient condition for capacity maximization is for all insurers to hold a net of reinsurance underwriting portfolio that is perfectly correlated with aggregate industry losses. Estimating capacity from insurers' financial statement data, they find that the U.S. insurance industry could adequately fund a $100 billion event in 1997. As a matter of comparison, Hurricane Katrina in 2005 cost the insurance industry $40 to $55 billion (2005 dollars). The hurricane's total cost was about $125 billion, indicating how low insurance coverage is for these losses. Moreover, at least 1,800 fatalities were reported with Katrina. Such events may also cause numerous insolvencies and severely destabilize the insurance markets. According to the authors, the prospect of a mega-catastrophe also brings with it a real threat of insurer failures and unpaid claims. Surviving insurers may have to reduce future sales of property liability insurance, causing price increases and availability problems. Some insurers may even leave the market (Born and Klimaszewski-Blettner, 2013).

Our main objective is to update this important study published in 2002 with new data that is available up to the end of 2020. We want to verify how the insurance market's capacity has changed over recent years. The rest of the paper is organized as follows. The next section presents recent developments on climate finance in the literature, while Section 2 discusses the importance of climate risk on the insurance industry. Section 3 reviews the main contributions in the insurance literature on climate risk, including the contribution of Cummins et al (2002). Section 4 presents the theoretical model proposed for estimating the insurance industry's capacity to compensate climate risk losses, and Section 5 presents our empirical estimates. We also document in detail the data and the methodology used to carry out our research. Section 6 concludes and proposes different avenues of future research. The online appendix contains additional data used for the robustness of the estimations.

1. Climate finance

Climate finance is defined by the United Nations Framework Convention on Climate Change (UNFCCC) as "local, national, or transnational financing—drawn from public, private, and alternative sources of financing—that seeks to support mitigation and adaptation actions that will address climate change" (reported in Hong et al, 2020). This financing is intended to change the world economy and build resilience to climate change.

Many financial sectors, spanning from banking and insurance to real estate, are directly impacted by the risks generated by tornadoes, wildfires, pandemics, and floods. This raises difficult questions, which were recently discussed in a special issue of the *Review of Financial Studies,* edited by Hong et al (2020): How can financial market prices mitigate risks from global warming? How can capital markets raise sufficiently large financing? How should the distribution of damages from catastrophic events be managed? However, no studies in finance or insurance have looked at the causal effects of climate change on the insurance industry, though various correlations have been documented.

Here is a typical question in the recent financial literature: Given the potential impact of climate change, are asset prices or firm values sensitive to exposure to climate risks? Three recent contributions address this important question on market efficiency in pricing these risks. Murfin and Spiegel (2020) use information on recent residential real estate transactions to determine whether house prices reflect the differential risks of sea level rise. They obtain limited house price effects with their methodology. In contrast, Baldauf et al (2020) use transaction data to measure the effect of flooding projections for individual homes and local measures of *beliefs* about climate change on house prices. They demonstrate that houses projected to be underwater are sold at a discount. Issler et al (2020) study wildfires in California between 2000 and 2018 with a comprehensive data set that merges information on fires, mortgages, property characteristics, and weather zones. Using the difference-in-differences approach, the authors find a significant causal increase in mortgage delinquency and foreclosure after fire events.

A crucial input for the analysis of climate change risks is the causal impact of climate events on economic activity, which is called the distribution of damages. This raises an important question about the modeling and sharing of extreme weather risks. Do extreme weather risks, such as the impact of Hurricane Sandy in 2012 or of the 2018 California wildfires, have long-run causal effects on insurance markets? These distributions of damages depend on location-based decisions by households and firms, and technological (self-protection and self-insurance) decisions in terms of preventing and mitigating the damages caused by disasters. They also depend on market insurance coverage (including moral hazard and adverse selection effects). By modeling these loss distributions adequately, the insurance industry should be able to play a critical role in facilitating risk-sharing and extending insurance coverage for extreme weather events. These research results should also improve public authorities' role in improving social resilience against climate risk (GAO, 2007; Postal, 2008; Hallegate, 2012, 2014).

2. Climate risk and the insurance industry

The potential causal impacts of new climate patterns on damages from catastrophe risks must be better estimated by the insurance industry and public authorities. These potential impacts may have been underestimated in risk management for many years. Here are some worldwide statistics obtained from the Munich Re reports of 2014, 2019, and 2021[1]:

- 88% of all natural events worldwide were weather-related between 1980 and 2014 (83% in 2019); and 40% of the overall losses from 1980 to 2014 occurred in Asia (43% in 2019).

- 64% of the insured losses were incurred in North America (incl. Central America and the Caribbean) during this period (35% in 2019), which represents about 30% of overall losses in this region, as in the rest of the world. Insurance penetration is low even in developed countries.

- Natural disasters accounted for $280 billion in losses around the world in 2021 ($120 billion insured). The record year was 2011, with $355 billion. About 10,000 deaths

[1] See also the different Sigma reports (2009, 2015, 2022).

were attributed to natural disasters in 2021. In the U.S., $145 billion in losses were observed, with $85 billion insured.

Climate risk was rated number one among the top-ten risks facing the insurance sector (Ernst and Young, 2008). The average over the last 10 years is $187 billion ($340 billion in 2017 only). The year 2019 was below the last 10-year average, with a total loss of $150 billion. However, the frequency has increased. In 2019, there were 33 events with more than $1 billion in total losses each. Nine events cost the insurance industry over $1 billion that year, and all of them were climate risk events (cyclones, storms with flooding, and tornadoes). Moreover, in April 2020, severe weather events in the U.S. cost insurers billions of dollars, with 14 tornadoes occurring— the fifth-highest monthly amount on record since 1950, according to the Aon *Global Catastrophe Recap* (2021).

In 2021, 22 weather and climate disasters of $1 billion and more were observed in the United States, for a total of $145 billion in damages. Since 1980, 310 events of $1 billion and more have accounted for $2.5 trillion, with an average of $148 billion over 2016–2021 (www.climate.gov/disasters2020).

Modeling firm AIR Worldwide now estimates that the losses to insured industry from Hurricane Ida in 2021 will range from $20 billion to $30 billion. The estimate includes wind and storm surge losses spanning from $17 to $25 billion, and private-market insured losses from inland flooding spanning from $2.5 billion to $5 billion. These estimates include insured physical damage to residential and commercial property and autos, but do not include National Flood Insurance Program losses. Most insured losses will be in the homeowner and commercial property lines of business in Louisiana and the Northeast, including New York and New Jersey. With an estimated $30 billion (and even $35 billion, according to other sources) in insurance losses, Ida is in the range of Hurricanes Andrew, Maria, and Harvey. State officials have reported more than 80 total deaths due to Ida.

The escalating frequency and severity of extreme weather-related events highlight a dangerous link between insurance risk and climate change, even if less than 40% of the total losses are covered. According to a PricewaterhouseCoopers survey conducted in 2017, natural catastrophes are now the second-highest risk insurance companies face, while global warming is ranked fourth. A more recent survey done by Deloitte (2020) found that most U.S. state insurance regulators expect all types of climate change risks to insurance companies to increase over the medium to long term. More than half the state regulators surveyed also indicated that climate change is likely to have a high impact on coverage availability and underwriting assumptions. U.S. state regulators and lawmakers are concerned about the insurance industry's response to climate change. Two traditional mechanisms are usually used to reduce financial fragility. Insurers can increase premiums in the states or counties most affected, or increase reinsurance coverage (Grenier, 2019). However, these two alternatives are not satisfactory to ensure the long-run stability of the industry.

We can summarize the major issues related to climate risks as follows (Dionne, 2015):

- For many years the population has concentrated in high-risk areas. This increases insurers' exposure to major catastrophes related to natural hazards (low frequency and high severity) (Grislain-Letrémy and Villeneuve, 2019; Goussebaïle, 2016).
- The demand for insurance coverage for climate risks among individuals is low (Arrow, 1982; Dixon et al, 2006; Wagner, 2020; Robinson and Botzen, 2022) because the potential insured underestimate the risk and are biased in estimating their net loss, due to anticipated government intervention. For example, although flood insurance has been subsidized by the U.S. federal government since 1968, demand remains low (Kousky, 2018; Landry and Jahan-Parvar, 2011).
- On the supply side, a survey funded by the National Association of Insurance Commissioners (NAIC) mentions that insurers reported increased engagement in climate-related activities over the recent years while they were not really prepared to cover climate risk in 2014 (NAIC, 2020). See also the study of Gatzert and Reichel (2022).
- Natural hazard losses fluctuate radically. This is a long-run issue. Insurers cannot restrict themselves to the recent loss history to calculate premiums and capital. They must compute, for example, the estimated maximum loss (EML) or the expected

shortfall, obtained from data over many years, and perform appropriate dynamic stress testing.

- Prevention is a long-run investment activity, yet insurance coverage is annual. This creates a problem of long-run commitment from the insurance industry to potential investors, leading to underinvestment in prevention.

- Insurers can spread their liabilities through reinsurance. In principle, the effects of catastrophes can be diversified through the worldwide reinsurance market. Historically, the capacity available to reinsurers was limited, but it has increased significantly since Hurricane Andrew (Cummins and Weiss, 2000, 2004).[2] Even if insurers and investors around the world are now more convinced that a lack of action to combat climate change is becoming costly in the long run, no real structural changes have been made. The current actions intended to reduce social climate-risk costs may not be the most efficient. In fact, some reinsurers have limited their exposure to such losses, and rating agencies seem to encourage such a move to maintain the current ratings of (re)insurance companies. Some reinsurers are more positive, however, but argue that this new environment is very complex, and that the reinsurance industry is learning how to improve its participation in these new environmental and economic realities (Kessler, 2015; Drexler and Rosen, 2022).

- Insurance-linked securities (ILS) are becoming important in the reinsurance market for catastrophe losses related to climate risk and earthquakes (Lakdawalla and Zanjani, 2012; Götze and Gürtler, 2022; Carayannopoulos et al, 2022). They are not very prevalent in the insurance market. ILSs can lower the cost of risk transfer in harsh (re)insurance market conditions. They help maintain (re)insurance capacity and offer multi-year protection. They limit credit risk by offering collateralization of losses. For investors, they are noncorrelated with other market, liquidity, and credit risks, so they represent an important diversification asset. Moreover, the capitalization of securities markets is much higher than that of (re)insurance markets. ILS penetration can reduce the price of insurance in the long run and increase the demand for insurance. However,

[2] On reinsurance, see Bernard (2013), Cummins et al (2021), Cummins et al (1997, 2001, 2013, 2021), Chen et al (2020), and Powell and Sommer (2017).

there is a long-run commitment issue regarding the participation of financial markets in climate risk after a big catastrophe. Will they stay in that risky market?

- Securitization and market consolidation are other market mechanisms that can improve market capacity (Cummins and Weiss, 2009; Cummins and Trainar, 2009; Boubakri and Triki, 2008; Berger et al, 2000; Akhigbe and Madura, 2001; Cummins et al, 1999; Cummins and Xie, 2006; Weiss and Chung, 2004; Weston et al, 2004).

Although estimates vary, it seems clear that a substantial gap exists between the existing reinsurance coverage and a catastrophic loss exceeding the \$15–20 billion range. For example, Swiss Re (1998) estimated that reinsurers would pay 39% of a once-in-a-century catastrophe loss in the U.S., such as a \$56 billion hurricane or a \$65 billion earthquake in California. The Swiss Re study estimated there was a worldwide total of \$53 billion in catastrophe excess-of-loss reinsurance in place in 1997. Cummins and Weiss (2000) show that the reinsurance industry could have funded \$60 billion of a \$100 billion above-expected loss.

According to 2014 data, the total reinsurance capital is about \$575 billion (\$660 billion, 2021), including \$62 billion in ILS capacity other than traditional reinsurance. Alternative capacity (ILS) includes collateral reinsurance, sidecar, industry loss warranty (ILW), and CAT bonds. As complements to reinsurance, they represented about 10% of the global catastrophe reinsurance capital in 2014 (250-year occurrence). We may think there is sufficient capacity because annual average long-run insured losses are around \$150 billion, but there have been significant recent exceptions, in 2011 (\$375 billion), 2017 (\$340 billion), and 2021 (\$343 billion) (AON, 2022)[3].

3. Academic research on climate risk and the insurance market[4]

[3] Exact statistics vary from one source to another but the ranges are comparable.

[4] See the special issue on climate risk and insurance published in 2022 by *The Geneva Papers on Risk and Insurance – Issues and Practice* for additional topics not discussed here, including applications in France (Charpentier et al, 2022) and in Japan (Shao, 2022).

The early academic contributions agree that natural catastrophes affect the insurance market and that this effect is increasing over time, probably because of global warming. Shelor et al (1992) and Lamb (1995) obtained contradictory results, however, on what effect natural catastrophes have on the insurance industry's profitability. Berz (1997) was one of the first to document the greenhouse effect on the insurance industry, concluding that the future of the insurance industry could be jeopardized if insurers do not adapt to the new climate conditions. Cummins et al (2002) show that unanticipated natural events may create liquidity problems in the short run and solvency problems in the long run for insurance companies.

In their theoretical analysis, Cummins et al (2002) propose a sufficient condition for capacity maximization: All insurers must hold a net of reinsurance underwriting portfolio that is perfectly correlated with aggregate industry losses. Estimating capacity using insurers' financial statement data, they find, from the data for 1983 to 1997, that the industry could adequately fund a $100 billion event, whereas U.S. insurers' equity capital was approximately equal to $350 billion in 2002. To provide an idea of the potential losses at that time, Hurricane Andrew (1992) represented a loss of $19 billion, while the Northridge earthquake (1994) cost more than $13 billion. Moreover, scenarios constructed in 1997 by catastrophe modeling firms suggest the feasibility of a $76 billion hurricane in Florida, a $21 billion hurricane in the Northeast, a $72 billion California earthquake, and a $101 billion New Madrid earthquake.

Cummins et al (2002) also show that the industry would be able to pay very high percentages of losses. For example, for a $20 billion catastrophe, they estimate that the industry could have paid at least 98.6% of the loss in 1997. The estimated percentages paid for larger losses declines, however. For example, according to their parameter estimates, the industry would be able to pay about 96.4% of a $100 billion loss based on the group sample and 92.8% based on the company sample. For a $200 billion loss, the industry could pay 84.0% based on the group sample and 78.6% based on the company sample.

Nonetheless, such events may cause numerous insolvencies and severely destabilize insurance markets. For instance, a $100 billion catastrophe is projected to cause 30 insolvencies for the group sample and 136 insolvencies for the company sample. The number of insolvencies at 1991 capitalization levels would be 108 groups and 216 companies. This means that many insurers were not ready for such potential catastrophes and may have become good targets for acquisition. Their data are taken from the regulatory annual statements filed by insurers with NAIC.

Moreover, they were able to estimate insurers' responses for different scenarios such as a Category-5 hurricane hitting Miami or a magnitude-8.2 earthquake in San Francisco. Their measure of capacity is based on how much equity or surplus is available and how effectively the riskiness of insurance losses is spread though the insurance market. The traditional instrument to spread risk between insurers is reinsurance. By buying and selling options on their portfolios with each other or with specialized reinsurers, insurers can change the risk characteristics of their portfolios.

However, there is a very large number of potential catastrophe scenarios, and the data requirements to conduct such an analysis for the entire insurance industry are enormous. Moreover, while such scenarios are valuable for planning at the firm level, they do not provide enough detail to assess the risk-spreading efficiency of the total insurance market. Rather, they seek a more general response function. Cummins et al (2002) estimate the distributional characteristics of catastrophic losses and allocate such losses to individual insurers using correlations and financial data. The result is an option-like function that defines the estimated deliverable insurance payments conditional on any given size of aggregate catastrophic loss, and that projects the number of insurer insolvencies that would result.

When capital and surplus levels are high, most insurers plan to use capital to make deals. According to a recent survey by KPMG (2018), about three-quarters of insurers expect to conduct an acquisition, and two-thirds plan to seek partnership opportunities over the next three years. Eighty-one percent say they will conclude up to three acquisitions or partnerships in the same period. As a top priority, 37% hope to transform their business models, 24% want to transform their operating model, and 10% are looking to acquire new innovative capabilities and emerging technologies through their acquisitions. The key goal is to obtain a deal that generates a contribution over the next 10 to 15 years.

A.M. Best manages a database of more than 1,000 insurance companies that have failed in the United States since 1969. The most common reasons for insolvency are deficient loss reserves, inadequate pricing, and rapid growth. Natural disasters are the seventh most common reason, accounting for 7% of insolvencies. The Financial Services Authority (FSA) in the United Kingdom assessed 270 insurance companies that failed in the European Union since 1969. Many factors were identified as primary or contributing factors, with natural hazards found to have made a small contribution. Yet, in both these studies, the data cover a very long period, and it is not clear that they are representative of the last 20 years.

Regarding other pertinent contributions, Anderson and Gardiner (2008) provide a guideline to help insurance companies manage climate risk. Availability and affordability are the major problems. Insurers alone cannot effectively reduce the social cost of climate risk. More coordination with governments is necessary for prevention. Another failure is the lack of a link between sustainability and disaster resilience. Insurers must be more active in unifying green and disaster-resilience efforts in sectors such as construction, agriculture, and land use (see also Hallegate, 2014).

Mills (2009) analyzes different mechanisms to improve the insurance industry's capacity to cover insurable losses: new coverage products, a better understanding of climate change, and the financing of activities intended to reduce climate risk. Gollier (2005) underscores the necessary role of government to reduce the fragility of the insurance industry when extreme events occur. He claims that the government should act as a reinsurer to reduce the number of bankruptcies, an assertion that does not corroborate the study by Mills (2009), who instead favors stronger private risk management[5] (see also Michel-Kerjan, 2012, 2015; Kunreuther, 2018; Aerts et al, 2014; Collier et al, 2021; Klein and Wang, 2009). Jametti and Ungern-Sternberg (2010) do not consider the observed risk selection

[5] On risk management in the insurance industry, see Cummins et al (2009), Bauer et al (2013), and Hoyt and Liebenberg (2011).

between the private and public sectors as optimal in cases where the private sector keeps acceptable or lower losses and the public sector is limited to extreme losses. Louass and Picard (2021) propose a new characterization of optimal insurance coverage for low-probability catastrophic risks. They derive determinants of insurability and socially optimal risk sharing for events that have a low probability and high severity, and that affect many individuals.

Born and Viscusi (2006) offer a different approach to analyze the effect of natural catastrophes on the insurance industry. Using data from the Swiss Re Sigma Reports for the 1984–2004 period, they show that small insurers are more likely to be affected, because they are less diversified. Finally, Born and Klimaszewski-Blettner (2013) affirm that some insurers tend to reduce their activities when they are subject to severe regulations or when they receive unanticipated large claims. The reduction-of-activities behavior is less frequent for large insurers that are better diversified.

4. Theory

Borch (1962) shows, in an expected utility (EU) framework, that value-maximizing risk-sharing transactions would leave all risk-averse insurers holding losses net of reinsurance portfolios defined solely on the market's aggregate loss, and that insurance would be priced solely on the correlation with this aggregate portfolio. Each insurer holds a proportion of the aggregate loss, and all insurers' portfolios are perfectly correlated. This result is obtained by assuming that transactions between insurers are costless. Extending this result to a world with risk neutrality and limited liability, Cummins et al (2002) show that the distribution of insurance liabilities, which minimizes insolvencies and therefore maximizes payments to policyholders, is similar to the Borch equilibrium. Their market structure provides a framework for measuring the insurance industry's available capacity to respond to major catastrophes.

Under limited liability and risk neutrality, the ability of the insurer *i* to pay the total insured loss $L_i^p = \mathrm{Min}\left(L_i ; E\left(L_i\right) + Q_i\right)$ depends on its equity capital Q_i and the collected premiums without transaction costs $E(L_i)$, where L_i is the total insured loss of insurer *i,* and $E(L_i)$ its expected value. The insurer has a put option on L_i with a corresponding strike value equal to available resources $E(L_i)+Q_i$, as illustrated in Figure 1.

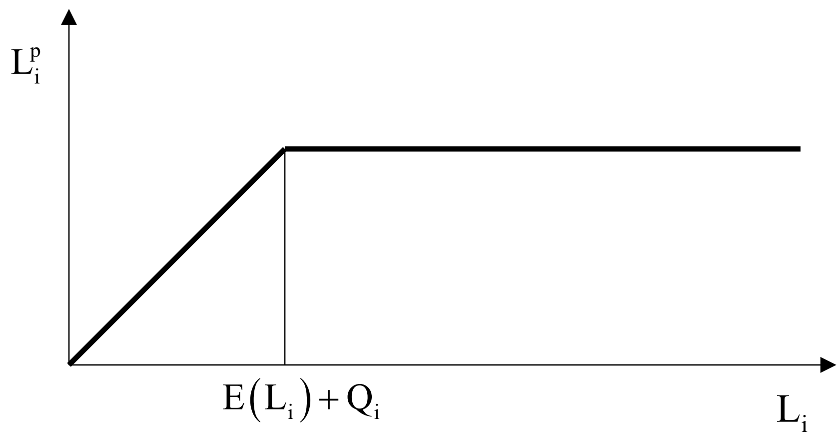

Figure 1

Aggregating these values under limited liability, they show that the aggregate loss that will be paid by the insurance industry to policyholders will be the minimum of the value of aggregate losses L and the industry's total resources, as shown in (1):

$$\sum_{i=1}^{N} L_i^p = \mathrm{Min}\left\{L; E(L)+\sum_{i=1}^{N} Q_i\right\}, \tag{1}$$

where N is the total number of insurers in the market, and $E(L)+\sum Q_i$ measures the total resources in the industry for expected and unexpected losses. Consequently, they obtain the following definition for maximizing payouts to policyholders.

Definition of the insurance industry's payment capacity: For any configuration of losses for which insurers are liable, the payment capacity of the insurance industry is the proportion of those liabilities that is deliverable, given the financial resources of the firms on which the losses fall and given all arrangements (such as reinsurance, guarantee funds, etc.) for reallocating those losses among insurers.

They then analyze the conditions for capacity maximization and obtain the following corollary.

Capacity maximization: When the necessary conditions of capacity maximization are satisfied, all insurers will hold losses net of reinsurance portfolios L_i that are perfectly correlated with aggregate industry loss *L*.

This provides a reference for measuring industry capacity. Let us define the proportional payment of aggregate loss *L* by insurer *i* as

$$\alpha_i L = c_i L_U + k_i D = L_i \tag{2}$$

where

α_i is the proportion of *L* paid by insurer *i*;

c_i is the proportion of the aggregate catastrophe risk L_U paid by insurer *i*;

k_i is the insurer *i* portion of the aggregate industry diversifiable losses *D*.

They show that (2) maximizes industry capacity for a given industry surplus *Q* when there is perfect correlation between L_i and *L*.

To estimate the industry observed response function, we must make distributional assumptions about *L*. Using the normal distribution, the response function is equal to

$$E\left(T_i \middle| Q_i, L\right) = \left(E\left(L_i\right) + Q_i - \mu_{L_i|L}\right) N\left[\frac{E\left(L_i\right) + Q_i - \mu_{L_i|L}}{\sigma_{L_i|L}}\right] + \sigma_{L_i|L}\frac{1}{\sqrt{2\pi}} e^{-(1/2)\left(\left(E(L_i)+Q_i-\mu_{L_i|L}\right)/\sigma_{L_i|L}\right)^2}$$

where

$$\mu_{L_i|L} = \mu_i + \frac{\rho_i \sigma_i}{\sigma_L}\left(L - \mu_L\right) \text{ and } \sigma^2_{L_i|L} = \sigma_i^2\left(1 - \rho_i^2\right), \tag{3}$$

and where T_i is the terminal equity of insurer *i,* $\mu_i = E\left(L_i\right)$, $\mu_L = E\left(L\right)$, and ρ_i is the correlation coefficient between L_i and *L*. The corresponding response function can be written as

$$R_i \mid L = E(L_i) + Q_i - E(T_i | Q_i, L) = (E(L_i) + Q_i) N(-C_i) + \mu_{L_i|L} N(C_i) - \sigma_{L_i|L} n(C_i), \tag{4}$$

where

$$C_i = \frac{E(L_i) + Q_i - \mu_{L_i|L}}{\sigma_{L_i|L}} \tag{5}$$

is the standardized capacity, $N(C_i)$ is the standard normal distribution function, and $n(C_i)$ is the standard normal density function. Using (4), we can measure the capacity of the industry for any industry loss L, as a function of two industry variables, $\{E(L), \sigma(L)\}$, and three firm variables, $\{\sigma_i, \rho_i, Q_i\}$, where ρ_i is the correlation coefficient between L_i and *L*. One can show that the expected response value is decreasing in σ_i and positively related to ρ_i. This occurs because the value of the insurer's nonpayment option is increasing in σ_i and because the industry gets closer to optimal compensation as ρ_i gets higher.

In summary, since (2) maximizes industry payment capacity for a given initial industry surplus *Q*, the estimated empirical correlations will provide an empirical measure of insurance industry capacity utilization for a given *Q*.

Figure 2 represents such a measure of average capacity (OZ) that has to be estimated where *X* is the estimated capacity utilization for an aggregate loss of $E(L)$ plus $30 billion, *W* would be the estimated capacity value for a less diversified industry, while *Y* would be for a more diversified industry.

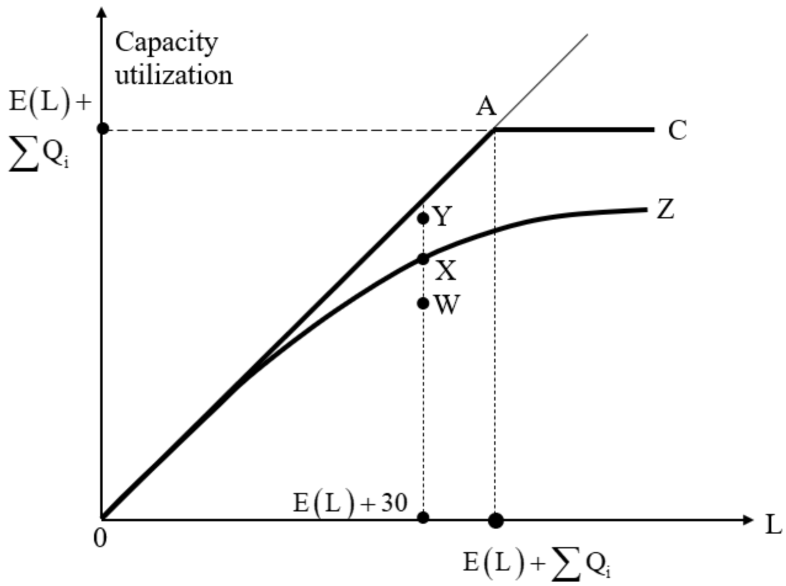

Figure 2

But many frictions in the market can reduce the conditions described in the corollary on capacity maximization, such as small insurer size, geographical distribution of insurers, loading in insurance pricing, reinsurance costs, and other insurer diversification costs. For example, they estimate the average transaction costs for reinsurance $(\text{price} - \text{expected loss})/\text{expected loss}$ to be equal to 65% during the ten years preceding their study.

5. Extension of the Cummins et al (2002) empirical analysis

5.1 Introduction

In their theoretical analysis, Cummins et al (2002) show that the condition for capacity maximization, given a level of total resources in the industry, is, for all insurers, to hold a net of reinsurance underwriting portfolio that is perfectly correlated with aggregate industry losses. Such a measure of capacity rests on two broad components: the size of the capital and industry diversification. How much equity or surplus is available? And how effectively is the riskiness of insurance losses spread through the insurance market? The main objective of this study is to update the computation of this correlation coefficient and measure the capital capacity of the U.S. insurance industry with new data up to the end of 2020.

We develop estimates of response functions for the U.S. property liability insurance industry by selecting samples of insurers and estimating the parameters of Eq. (4). The response functions are then calculated for various values of *L*, the total industry loss that can be observed during different years. The objective of the analysis is to determine the ability of the U.S. insurance industry to respond to catastrophic losses, and to measure the industry's capacity to spread risk across the market. This section discusses the method we use to measure industry capacity as well as sample selection, parameter estimation, and estimation results.

The fact that some insurers do not write insurance covering catastrophes, or do not do business in catastrophe-prone areas or happen to be lucky in suffering relatively low losses as a result of a given event is captured by the estimated correlation coefficient ρ_i between company *i* and industry losses. To the extent that differences in loss correlations can be under or over for these features of industry loss exposure and experience, these estimates must be viewed as approximations.

The data for the study is taken from the regulatory annual statements filed by insurers with the NAIC. In Cummins et al (2002), the capacity estimates are for 1997, the most recent report year available at the time the study began. To estimate parameters, Cummins et al (2002) use data from the period of 1983 to 1997, providing 15 annual observations on the companies in the sample.

The losses used in estimating capacity are net losses incurred, defined as direct losses incurred plus losses due to reinsurance assumed minus losses due to reinsurance ceded. Direct losses incurred are losses paid or owed directly to policyholders, while net losses incurred reflect the netting out of reinsurance transactions. Our analysis thus does not take into account the direct effects of reinsurance on capacity. There may be some indirect effects, as discussed in the conclusion. We use the value from line 2 to line 11 of column 28 in Schedule P – Part 1 – Summary. It is the net losses and loss expenses incurred during a year. In what follows, net losses (for short) and net losses plus loss expenses should be considered synonymous.

5.2 Sample selection and modeling approach

It was not possible to create a 15-year database for the same time period as in Cummins et al (2002) to make a direct comparison. Our data period is from 1990 to 2020, while their data period is from 1983 to 1997. They used the 15-year period to estimate their parameters. One way to compare our results to theirs is to employ the observations from line 2 to line 11 at column 28 in Schedule P – Part 1 – Summary of NAIC reports, providing 10 annual observations on the companies. We label this sample "Sample 1", which represents the main source of data for this study. One question we asked was how the results might differ when we use 10 annual observations instead of 15 as in their study?

To answer this question, we first estimated our parameters over 10 years. We concentrated the comparison on three ten-year periods, respectively from 1996 to 2005, 2005 to 2014, and 2011 to 2020, using data at line 11 at column 28 in Schedule P – Part 1 – Summary of NAIC reports, providing 10 annual observations on the companies. We label this sample "Sample 2." The details are presented in Online Appendix 2. We compare these results from Sample 2 with those from Sample 1 to verify how parameter estimates can be affected by the type of data used in the estimations (line 2 to line 11 versus line 11 only).

Second, again for the years 2005, 2014, and 2020, we estimate the parameters for three 15-year periods from 1991 to 2005, 2001 to 2014, and 2006 to 2020, with the values from line 11 at column 28 in Schedule P – Part 1 – Summary of NAIC reports, providing 15 annual observations on the companies. We called this sample "Sample 3." The details are presented in Online Appendix 3. We then compared these results with those estimated from Sample 2 to verify how parameters can be affected by the length of the estimation period.

Two data series are available. Full-time series (FTS) are companies present in the samples for the entire period and having net losses and equity capital strictly greater than 0 each year. Regression models are estimated to provide parameter estimates for firms that are not in the full-time series (NFTS). Parameters for these companies are estimated by inserting their 1997, 2005, 2014, and 2020 financial data into the regression models. Observations for net admitted assets and total liability had to be strictly greater than zero, while those for cash and short-term investments and for liquid asset had to be greater than or equal to zero.

Sample 1 is our main sample. All main estimates presented in the following discussion are derived from this sample. Sample 2 and Sample 3 are for robustness analysis. They show that results in Sample 1 are not dependent of the type of data (line 2 to line 11 instead of line 11 only) nor of the methodology (10 years instead of 15 years).

5.3 Raw data from Sample 1

Tables A1 to A4 in the Appendix report net losses and capital for Sample 1 during the 1990–2020 period. We can see from tables A1 and A3 that the number of companies significantly decreases after 2015. Also, the mean of the net losses increases by year, with few exceptions. Summary statistics on equity capital, the other determinant for computing industry capacity, are presented in tables A2 and A4 for the same period. Equity capital increased significantly during the period of analysis.

Table 1: FTS Sample 1
Summary statistics: Net losses and equity capital
($000 omitted)

Sample	Net losses incurred	Equity capital	Number of firms
1997			
Groups & unaffiliated companies	201,252,911	355,097,195	877
All companies	201,252,911	355,097,195	1,667
2005			
Groups & unaffiliated companies	301,274,767	496,797,400	853
All companies	301,274,767	496,797,400	1,578
2014			
Groups & unaffiliated companies	343,463,626	780,443,239	844
All companies	343,463,626	780,443,239	1,574
2020			
Groups & unaffiliated companies	455,137,413	1,085,524,198	841
All companies	455,137,413	1,085,524,198	1,509

Table 1 and Table 2 report net losses and equity capital for FTS and NFTS data in different years for all companies and for groups and unaffiliated companies. For the moment, only the number of firms differs between the two types of companies, but it will be interesting to observe their respective diversification behavior. Table 2 also compares our data with those of Cummins et al (2002) for the year 1997. We observe that our estimates are quite similar. The net losses in 1997 are equal to $202 billion for 2,256 insurance companies in their study, while it is equal to $210 billion for 2,286 insurance companies in our database during the same period. It increases to $461 billion for 1,787 insurers in 2020, while capital increased more rapidly during the same period. The ratio of net losses over capital decreased over the years. For example, in Table 1 (Table 2), the ratio of net losses incurred over equity capital was 57% (56%) in 1997 and 42% (41.5%) in 2020.

Table 2: NFTS Sample 1
Summary statistics: Net losses and equity capital
($000 omitted)

Insurance industry	Net losses incurred	Equity capital	Number of firms
1997			
Cummins et al 2002 study			
Groups & unaffiliated companies	201,905,979	370,993,421	1,248
All companies	201,905,979	370,993,421	2,256
Our database			
Groups & unaffiliated companies	209,800,900	373,035,693	1,179
All companies	209,800,900	373,035,693	2,286
2005			
Groups & unaffiliated companies	311,568,085	520,451,387	1,200
All companies	311,568,085	520,451,387	2,152
2014			
Groups & unaffiliated companies	349,123,503	803,479,225	1,064
All companies	349,123,503	803,479,225	1,923
2020			
Groups & unaffiliated companies	461,350,387	1,109,446,600	992
All companies	461,350,387	1,109,446,600	1,787

5.4 Capacity estimation

Let $L_t = \sum_i L_{it}$ be the total industry net losses in year *t*. The estimator of the mean of net losses for the industry is equal to $\overline{L} = 1/T \sum_i L_t$ and the estimator of the variance of net losses for the industry is equal to $\hat{\sigma}^2 = \frac{1}{T-1}\sum_{t=1}^{T}\left(L_t - \overline{L}\right)^2$. We write $\hat{\sigma}$ for the standard deviation of the net losses for the industry. Table A5 presents the total net losses, their means, and their standard deviations over the period 1990–2020 for the FTS population.

Detailed values for $\hat{\sigma}_i$ are presented in Table A6. The correlation coefficient between company *i*'s losses and the industry losses is estimated using the following formula:

$$\hat{\rho}_i = \frac{\frac{1}{T-1}\sum_{t=1}^{T}\left(L_{it} - \bar{L}_i\right)\left(L_t - \bar{L}\right)}{\hat{\sigma}_i \hat{\sigma}}. \tag{6}$$

On average, the standard deviation of the net losses incurred by a company is less than \$30 million from 1990 to 2001, increases to \$44 million in 2008, decreases to \$39 million in 2014, and increases to about \$50 million during the last three years of observation. We can see from Table A7 that, on average, the correlation coefficient between company *i*'s losses and the industry losses is 0.5996 in 1990, decreases to 0.4071 in 1999, decreases to 0.3683 in 2010, and increases beyond 0.4000 during the last four years.

5.5 Detrended parameter estimates

The detrended estimates are based on the residuals from time trend regressions. The reason for computing the detrended estimators is that property liability insurance losses are subject to a strong positive time trend. Thus, the raw estimates of the loss standard deviation capture trend-related growth in losses across years. Differences in losses across years due to this trend effect are thus anticipated loss fluctuations and should not be included when measuring the effect of catastrophes and other types of random shocks on the insurance market's capacity.

By measuring capacity using both the raw and detrended parameters, we can isolate potential time-trend bias. Detrended estimates of $\hat{\sigma}_i^2$ and $\hat{\sigma}^2$ are obtained by applying formulas (7) and (8) to the estimated residuals ε_{it} and ε_i obtained, respectively, from (6). The detrended estimate of $\hat{\rho}_i$ is obtained by applying formula (9) to the estimated residual series ε_{it}, and ε_i from (6).

To obtain the detrended parameter estimates, we first conduct the following regressions:

$$L_{it} = \alpha_{0i} + \alpha_{1i} t + \varepsilon_{ii}$$

$$L_t = \alpha_0 + \alpha_1 t + \varepsilon_t . \tag{6}$$

The detrended estimator of the variance of losses for the industry is equal to

$$\det \hat{\sigma}^2 = \frac{1}{T-1} \sum_{t=1}^{T} \left(\hat{\varepsilon}_t - 0 \right)^2 . \tag{7}$$

We write *det* $\hat{\sigma}$ for the detrended estimator of the standard deviation of the losses for the industry. The detrended estimator of the variance of losses for company *i* is equal to

$$\det \hat{\sigma}_i^2 = \frac{1}{T-1} \sum_{t=1}^{T} \left(\hat{\varepsilon}_{it} - 0 \right)^2 . \tag{8}$$

The detrended correlation coefficient between company *i*'s losses and the industry losses is estimated using the following formula:

$$\det \hat{\rho}_i = \frac{\frac{1}{T-1} \sum_{t=1}^{T} \left(\hat{\varepsilon}_{it} - 0 \right)\left(\hat{\varepsilon}_t - 0 \right)}{\det \hat{\sigma}_i \det \hat{\sigma}} . \tag{9}$$

On average, Table A8 indicates that the detrended standard deviation of the net losses incurred for a company is less than \$15 million from 1990 to 2000, increases up to \$22 million in 2007, and is beyond \$25 million afterward, reaching \$28 million in 2020, this last value being about three times the value of 1999.

We can see from Table A9 that, on average, the detrended correlation coefficient between company *i*'s losses and the industry losses is 0.2020 in 1990 and decreases to 0.0891 in 2007, then increases from 0.1760 in 2008 and to 0.2419 in 2020. The estimated detrended correlation coefficients in Table A9 are much lower than those observed in Table A7, indicating a real time-trend bias in the raw data.

5.6 Regression models for parameter estimations

Regression models estimate the parameters of the companies that did not have data for the full time period covered by the study (NFTS companies). The procedure is to estimate regression models with the parameters of the FTS companies as dependent variables and companies' financial characteristics as regressors. The NFTS company parameters are computed by inserting the financial characteristics of these firms into the equation to obtain fitted parameter values, which are used in estimating the insurance industry capacity.

We need to estimate the parameters $\{\hat{\sigma}_i, \hat{\rho}_i\}$ for companies that do not have the FTS period covered. Since those parameters are censored at 0 for the standard deviation and censored to -1 and 1 for the correlation coefficient, we estimated the tobit model (censored normal regression) to obtain the parameters values.

For the 1997 market, we report the results of these regressions in Table A10a for the standard deviation and in Table A11a for the correlation coefficient. For the 2005 market, we report the results of these regressions in Table A10b for the standard deviation and in Table A11b for the correlation coefficient. Similar results are obtained for the years 2014 and 2020. They are reported in panels c and d of tables A10 and A11.

By inserting the financial characteristics of the NFTS firms into the estimated equations, we obtain fitted parameters $\hat{\sigma}_i$ and $\hat{\rho}_i$. Table A12 presents the summary statistics for the standard deviation of the net losses incurred for a company, by year, for the NFTS Sample. Table A13 presents the summary statistics for the correlation coefficient between company *i*'s losses and the industry losses, by year, for the NFTS Sample.

The average values of the raw and detrended parameter estimates for all companies and groups and unaffiliated companies are presented in Table 3 for the FTS and NFTS samples. As anticipated, the detrended values of sigma and correlation coefficients are much lower than the raw values. The detrended standard deviations and correlations are higher in 2020 than those in previous years. Detrended sigmas are higher for groups and unaffiliated companies, while detrended correlations are lower after 2014.

Table 3: Detrended and raw parameter estimates: Property liability insurance industry
with values from Sample 1

Case	Average				Number of firms
	Detrended sigma × 10^8	Detrended correlation	Raw sigma × 10^8	Raw correlation	
1997					

Insurance industry (FTS)					
Groups & unaffiliated companies	0.1766	0.1141	0.3703	0.5092	877
All companies	0.1311	0.1257	0.2536	0.4390	1,667
Insurance industry (NFTS)					
Groups & unaffiliated companies	0.2066	0.1243	0.4320	0.4899	1,179
All companies	0.0955	0.1004	0.2935	0.4376	2,286
2005					
Insurance industry (FTS)					
Groups & unaffiliated companies	0.3198	-0.0077	0.6241	0.5110	853
All companies	0.2157	0.0545	0.3969	0.4609	1,578
Insurance industry (NFTS)					
Groups & unaffiliated companies	0.3629	0.0352	0.7009	0.4765	1,200
All companies	0.1582	0.0409	0.4245	0.4399	2,152
2014					
Insurance industry (FTS)					
Groups & unaffiliated companies	0.3872	0.1162	0.6258	0.3927	844
All companies	0.2582	0.1621	0.3912	0.4039	1,574
Insurance industry (NFTS)					
Groups & unaffiliated companies	0.4202	0.1233	0.6817	0.3489	1,064
All companies	0.2113	0.1337	0.4156	0.3848	1,923
2020					
Insurance industry (FTS)					
Groups & unaffiliated companies	0.4135	0.1690	0.8693	0.4282	841
All companies	0.2804	0.2419	0.5348	0.4668	1,509
Insurance industry (NFTS)					
Groups & unaffiliated companies	0.4299	0.1716	0.9699	0.4138	902
All companies	0.2368	0.2093	0.5811	0.4487	1,787

Note: FTS: Full Time Sample. NFTS: Non Full Time Sample.

As expected, detrending reduces the magnitude of loss standard deviations and the correlations between companies and industry losses. Because detrending leads to larger reductions in correlations than in the standard deviations, we expect the estimated loss payments to be lower for the detrended parameter estimates than for the raw estimates.

5.7 Response function for industry capacity

The response function is calculated for various values of L, the total industry net loss. The response functions for the insurance industry Sample 1 are shown in figures 3 and 4 for 1997 and 2020 respectively. Those of 2005 and 2014 are reported in Online Appendix 1 (figures O1 and O2). This sample is composed of firms that have full time series (FTS). The corresponding four figures for the NFTS are in Online Appendix 1 (figures O3, O4, O5, and O6). The horizontal axis measures possible values for aggregate insurance industry net losses. The vertical axis measures the amount paid by all firms considered.

The figures show the estimated amounts that would be paid for the industry losses, spanning from the actual expected losses and adding unexpected losses for a given year: spanning from \$200 billion to \$500 billion in 1997; from \$300 billion to \$600 billion in 2005; from \$340 billion to \$740 billion in 2014; and from \$460 billion to \$1,260 billion in 2020. These limits were chosen from the total observed losses for the U.S. property liability insurance industry during the corresponding year and the total equity capital for that year. Four response curves are shown in each figure based on raw and detrended parameters for group and company samples. Our main interpretation will be for detrended parameters for all companies.

The existing market capacity departs from the Borch theorem result that losses are perfectly correlated and insurers are evenly capitalized. Figure 3 shows that the 1997 response curve with detrended FTS data begins to diverge from the 45° line at approximately \$220 billion and that the 2020 response curve begins to diverge from the 45° line at approximately \$620 billion, meaning the insurance industry can easily cover an extra loss of \$200 billion in 2020.

The corresponding numbers for realized capacity are presented in Table 4. Realized capacity is obtained as the ratio, at the chosen loss level, of the value of the response curve Z to the value of the maximum curve C. We observe that all companies in the FTS sample were able to pay 93% of a \$100 billion loss in 1997, but only 81% for a \$200 billion loss. Cummins et al (2002) obtained 93% and 79%, respectively, with their data in 1997 (see their Figure 4). In 2020, the percentages are 99.5% and 98%. We also observe that, in 2020, the industry seems to be able to cover 89% of a $400 billion event during a year or, possibly, for 2 events of $200 billion each.

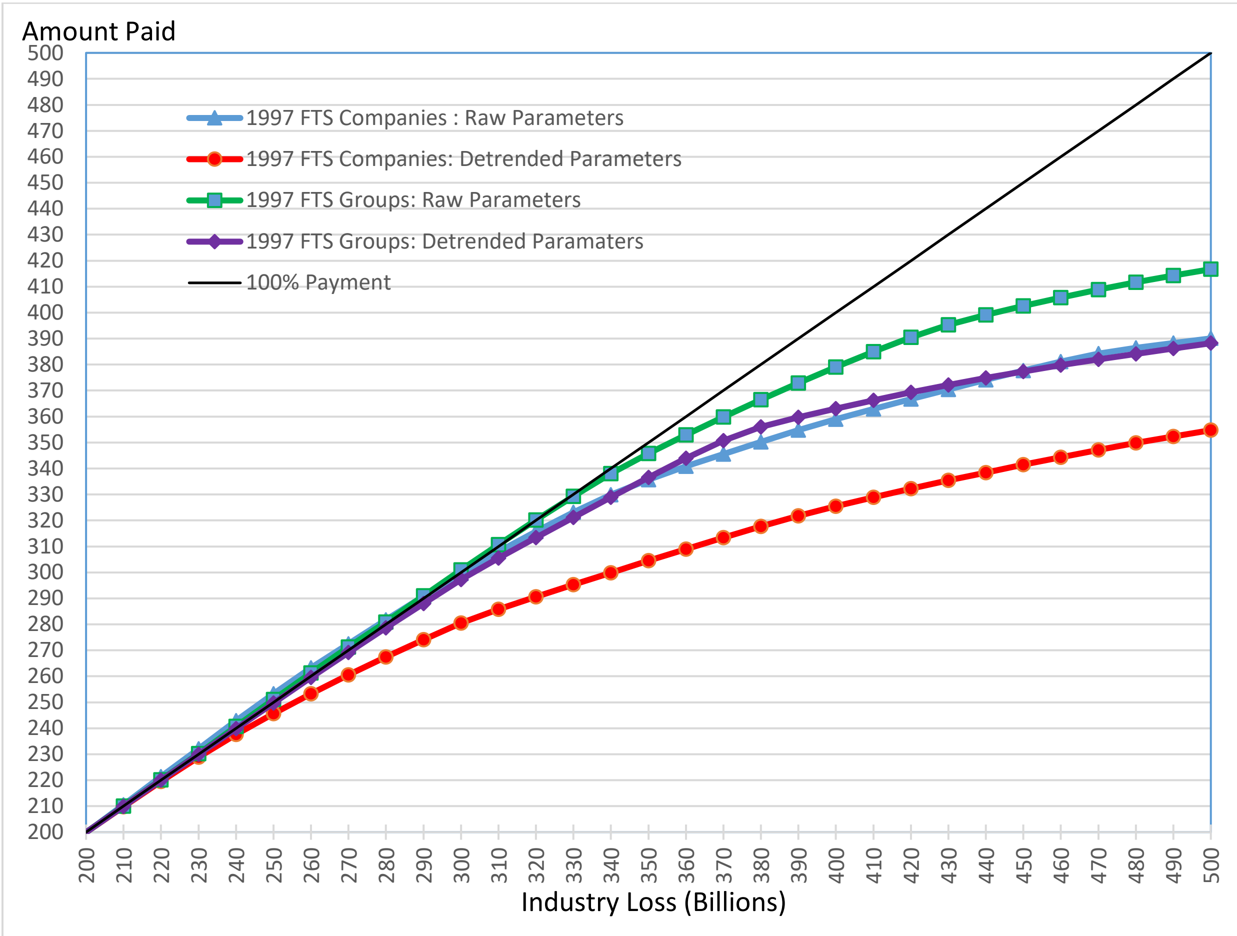

Figure 3: Industry capacity in 1997

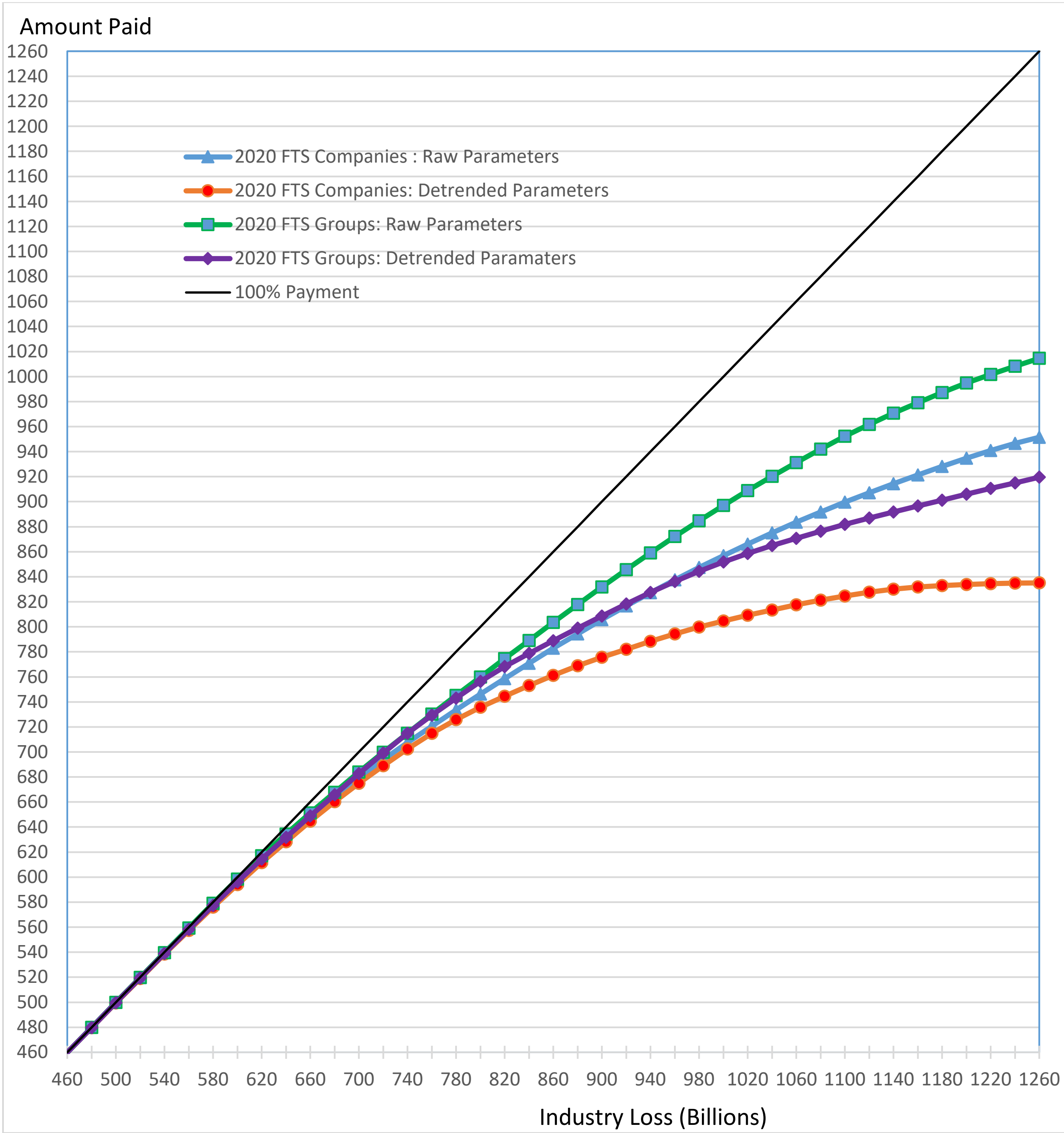

Figure 4: Industry capacity in 2020

Table 4 Capacity from Sample 1 with detrended values

	%			
1997	100 billion	200 billion	300 billion	400 billion
Insurance industry (FTS)				
Groups & unaffiliated companies	99.0	90.8	77.6	67.1
All companies	93.3	81.3	70.9	62.2
Insurance industry (NFTS)				
Groups & unaffiliated companies	94.7	87.9	77.3	67.0
All companies	94.6	82.8	72.4	63.5

	%			
2005	100 billion	200 billion	300 billion	400 billion
Insurance industry (FTS)				
Groups & unaffiliated companies	97.9	90.5	82.2	75.3
All companies	95.3	85.1	74.3	65.0
Insurance industry (NFTS)				
Groups & unaffiliated companies	95.8	90.7	83.3	77.1
All companies	97.3	89.2	80.3	72.9

	%			
2014	100 billion	200 billion	300 billion	400 billion
Insurance industry (FTS)				
Groups & unaffiliated companies	99.2	96.6	91.5	85.5
All companies	98.5	94.6	87.8	80.5
Insurance industry (NFTS)				
Groups & unaffiliated companies	97.7	94.8	90.5	85.2
All companies	99.0	95.7	89.7	83.1

	%					
2020	100 billion	200 billion	300 billion	400 billion	500 billion	600 billion
Insurance industry (FTS)						
Groups & unaffiliated companies	99.6	98.3	95.9	91.7	87.1	82.1
All companies	99.5	97.7	94.1	88.5	82.7	77.1
Insurance industry (NFTS)						
Groups & unaffiliated companies	98.9	97.3	94.9	91.2	86.6	82.1
All companies	99.9	98.8	95.9	91.0	85.8	80.8

6. Conclusion

The main objective of this study is to estimate the observed capacity of the U.S. property liability insurance industry to cover climate risk losses in 2020 and to verify how this capacity has evolved since 1997. We also present all important steps in data management and model estimation for those who want to replicate the analysis or update the results, because climate risk is destined to become a significant research subject over the coming years.

Cummins et al (2002) use Borch's theorem as starting point for defining industry capacity. They extend the theorem to a limited liability framework with risk neutrality. Capacity maximization is obtained when each insurer has an underwriting portfolio perfectly correlated with the industry aggregate loss. At Pareto optimality, the industry would pay 100 percent of losses, up to the point where industry net premiums and equity are exhausted. This theoretical result does not consider the different frictions in the insurance market, including transaction costs, asymmetric information, and the relative exposure of insurers to climate risks. Moreover, insurers are unevenly capitalized, such that some may go bankrupt for relatively low levels of industry losses. Finally, most insurers are not perfectly diversified geographically and may have their exposures concentrated in a subset of states that are unevenly exposed to climate risk. The estimated correlations should consider all these imperfections and be used to estimate the real capacity of the industry.

Equity capital in the U.S. insurance industry increased from $355 billion in 1997 to $1.1 trillion in 2020 in the FTS Sample, and the ratio of net losses over capital decreased from 57% to 42%, indicating a better capitalisation in 2020. These ratios do not necessary measure the capacity of the insurance industry to cover additional unforeseen large events during a given year.

Although the insurance industry's available capital has increased significantly since 1997, the ability of the market to adequately insure catastrophic risks can be still problematic. The total available capital is for all types of insurable risks, not only for catastrophic events.

The industry response curves for 2020 are presented in Figure 4 for the FTS data. The curves assume that insurer losses are normally distributed and are estimated over a period of 10 years. The figure shows the response curves for industry losses spanning from $460 billion (total losses in 2020) to a maximum of $1.2 trillion (total capital in 2020). As documented in Table 4, results with detrended parameters indicate that the insurance industry can cover 98% of a $200 billion loss and 94% of a $ 300 billion loss. Table 4 also indicates that the capacity for a $300 billion loss would have been 71% in 1997 (74% in 2005 and less than 90% in 2014).

Table 4 also shows that the capacity accessible to groups and unaffiliated companies is always higher than for all companies with FTS data. The increase in capacity is attributable both to the higher absolute value of industry capitalization and, probably, the higher concentration of equity among the largest reinsurers, resulting from consolidation.

Many extensions of our analysis can be considered. Reinsurance is important in order to diversify climate risks around the world over time (Cummins and Weiss, 2000, 2004). To date, the two levels of industry capacity have been studied separately in the literature. It is documented that the presence of reinsurance can affect insurers' behavior (Desjardins et al, 2022). It would be interesting to analyse how insurers with more reinsurance coverage can obtain more capital and be more aggressive in taking on climate risk. The opposite causality link is also of interest.

Assuming normality for climate risk losses is a strong assumption. Cummins et al (2002) assumed a normal distribution to simplify the aggregation of individual losses. The true empirical distribution should have a loss distribution with a relatively high probability for extreme outcomes. Fat tails imply a strong influence of extreme observations on expected future risk. By using the same assumption in this study for replication, we may have overestimate industry capacity.

Cummins and Weiss (2000) explicitly considered the effect of reinsurer industry consolidation on the industry's capacity to cover catastrophe risks and verified a positive statistical link. Two research questions can be considered for the insurance industry: Is catastrophe risk a causal factor of industry consolidation? If so, how could this consolidation affect the insurance industry's capacity to cover climate risks, improve insurer value, and modify the demand for reinsurance?

Another issue concerns life insurance. Are life insurers prepared to deal with this increasing risk? How could extreme losses, related to climate risks involving many deaths, affect the future viability of life insurers' current business and investment portfolios? Another interesting research subject is how life insurers manage their investments in green technologies, since they are important investors that can influence global warming in the long run. Other financial market participants can also affect climate risk coverage, as well as global warming in the long run.

Finally, the starting point of Cummins et al (2000) was coverage for the "big one." But many big ones in a given year, or even simultaneously, must be considered in the near future, for instance a hurricane in Florida and an earthquake in California. This requires a more dynamic view of the evolution of industry capacity, particularly for losses associated to climate risk because many of these losses are related to global warming suspected to increase both the frequency and the severity of climate catastrophes!

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Appendix 1

Table A1: NFTS Sample 1
Summary statistics: Net losses and loss expenses incurred by year (1990–2020)
($000 omitted)

Year	N	Sum	Mean	Std	Max
1990	2,214	177,715,603	80,269.02	517,537.57	16,958,127
1991	2,241	182,530,805	81,450.60	524,570.85	17,027,661
1992	2,255	198,401,990	87,983.14	594,516.08	18,314,940
1993	2,252	190,413,917	84,553.25	554,470.02	19,155,972
1994	2,267	208,572,216	92,003.62	625,799.82	21,810,622
1995	2,280	204,910,538	89,873.04	600,634.17	21,432,510
1996	2,285	215,009,405	94,096.02	619,391.36	21,454,575
1997	2,286	209,800,900	91,776.42	594,148.82	20,713,399
1998	2,277	221,006,627	97,060.44	613,220.30	21,053,347
1999	2,213	227,814,550	102,943.76	637,275.50	21,203,854
2000	2,165	241,115,798	111,369.88	702,301.10	23,335,985
2001	2,137	265,470,813	124,225.93	770,202.56	25,798,108
2002	2,103	265,383,948	126,193.03	799,293.80	27,672,128
2003	2,101	277,826,866	132,235.54	815,773.37	27,807,298
2004	2,143	291,800,571	136,164.52	807,959.99	27,059,473
2005	2,152	311,568,085	144,780.71	907,532.39	29,846,734
2006	2,193	294,508,283	134,294.70	792,433.87	25,459,006
2007	2,223	312,562,459	140,603.90	821,870.35	26,371,754
2008	2,246	356,466,021	158,711.50	912,082.83	28,142,990
2009	2,207	325,036,521	147,275.27	883,359.23	28,701,847
2010	2,163	323,710,757	149,658.23	910,450.20	29,717,899
2011	2,119	358,938,218	169,390.38	988,525.45	30,474,865
2012	2,069	347,978,308	168,186.71	971,028.53	30,204,525
2013	2,016	334,899,331	166,120.70	982,821.13	31,447,613
2014	1,923	349,123,503	181,551.48	1,078,925.03	32,970,073
2015	1,953	363,651,857	186,201.67	1,115,894.90	34,203,391
2016	1,911	388,339,598	203,212.77	1,247,026.09	38,768,776
2017	1,864	425,020,127	228,015.09	1,327,374.43	38,816,047
2018	1,825	443,081,776	242,784.53	1,319,597.25	36,187,577
2019	1,805	454,609,413	251,861.17	1,361,103.60	36,311,052
2020	1,787	461,350,387	258,170.33	1,319,821.69	31,865,776

Note: NFTS: Non Full Time Sample.

Table A2: NFTS Sample 1
Summary statistics: Equity capital by year (1990–2020)
($000 omitted)

Year	N	Sum	Mean	Std	Min	Max
1990	2,214	168,699,802	76,196,840	472,348,721	8,338	17,889,083
1991	2,241	186,953,809	83,424,279	510,424,406	34,590	19,721,100
1992	2,255	195,366,490	86,637,024	500,682,734	58,072	18,751,399
1993	2,252	218,854,119	97,182,113	571,898,345	39,869	21,269,733
1994	2,267	228,726,897	100,894,088	573,638,353	64,388	21,143,916
1995	2,280	271,399,695	119,034,954	713,469,098	61,413	25,119,972
1996	2,285	302,009,404	132,170,418	853,921,858	3,312	30,053,793
1997	2,286	373,035,693	163,182,718	1,114,775,272	57,676	37,608,321
1998	2,277	408,329,033	179,327,639	1,219,263,145	56,100	41,766,158
1999	2,213	411,257,452	185,837,078	1,293,516,874	25,092	45,762,499
2000	2,165	382,656,656	176,746,723	1,226,322,767	10,794	43,690,982
2001	2,137	357,016,768	167,064,468	1,047,018,997	143,495	37,989,955
2002	2,103	354,836,839	168,728,882	956,411,831	64,294	31,600,584
2003	2,101	425,132,845	202,347,856	1,220,459,146	44,444	39,980,587
2004	2,143	477,012,026	222,590,773	1,388,012,845	773	46,144,210
2005	2,152	520,451,387	241,845,440	1,489,481,919	107,237	50,187,253
2006	2,193	590,617,960	269,319,635	1,735,785,286	246,477	58,034,267
2007	2,223	635,480,463	285,866,156	1,849,520,833	147,828	63,577,269
2008	2,246	573,351,952	255,276,916	1,553,939,706	18,159	53,273,951
2009	2,207	637,141,360	288,691,147	1,791,981,956	161,832	58,180,271
2010	2,163	681,298,429	314,978,470	2,233,559,244	7,935	68,437,054
2011	2,119	677,006,054	319,493,183	2,268,255,591	45,506	70,155,427
2012	2,069	717,940,204	346,998,649	2,521,352,060	15,406	78,861,514
2013	2,016	788,520,341	391,131,122	3,007,903,532	1,250	97,226,051
2014	1,923	803,479,225	417,825,910	3,106,439,268	1,153	93,997,651
2015	1,953	817,507,743	418,590,755	3,058,316,598	1,853	89,828,618
2016	1,911	855,520,039	447,681,862	3,355,687,237	77,634	101,285,906
2017	1,864	913,820,806	490,247,214	4,003,976,828	77,103	128,562,565
2018	1,825	902,810,027	494,690,426	3,991,042,469	106,638	122,471,086
2019	1,805	1,034,756,900	573,272,544	5,092,094,304	256,147	167,718,678
2020	1,787	1,109,446,600	620,843,073	5,648,877,364	167,443	187,762,294

Note: NFTS: Non Full Time Sample.

Table A3: FTS Sample 1
Summary statistics: Net losses and loss expenses incurred by year (1990–2020)
($000 omitted)

Year	N	Sum	Mean	Std	Max
1990	1,389	171,374,407	123,380	649,457	16,958,127
1991	1,444	176,052,958	121,920	649,801	17,027,661
1992	1,461	190,313,741	130,263	734,674	18,314,940
1993	1,488	181,856,782	122,216	678,362	19,155,972
1994	1,503	198,108,492	131,809	764,545	21,810,622
1995	1,560	195,420,453	125,270	722,705	21,432,510
1996	1,624	206,486,353	127,147	731,219	21,454,575
1997	1,667	201,252,911	120,728	692,404	20,713,399
1998	1,677	210,282,050	125,392	710,668	21,053,347
1999	1,663	216,479,256	130,174	73,1245	21,203,854
2000	1,639	229,485,981	140,016	80,2925	23,335,985
2001	1,636	256,830,748	156,987	87,6945	25,798,108
2002	1,615	257,085,229	159,186	90,8798	27,672,128
2003	1,595	268,3442,00	168,241	93,2563	27,807,298
2004	1,596	279,0725,93	174,858	93,0456	27,059,473
2005	1,578	301,274,767	190,922	105,5190	29,846,734
2006	1,589	285,720,875	179,812	92,6317	25,459,006
2007	1,604	300,912,718	187,601	96,0956	26,371,754
2008	1,626	345,168,298	212,281	1,065,100	28,142,990
2009	1,613	316,309,049	196,100	1,028,716	28,701,847
2010	1,596	315,294,344	197,553	1,055,586	29,717,899
2011	1,609	351,449,025	218,427	1,129,794	30,474,865
2012	1,612	341,523,488	211,863	1,096,009	30,204,525
2013	1,604	327,588,106	204,232	1,098,294	31,447,613
2014	1,574	343,463,626	218,211	1,189,212	32,970,073
2015	1,632	357,822,910	219,254	1,217,658	34,203,391
2016	1,609	381,780,711	237,278	1,355,884	38,768,776
2017	1,591	419,052,497	263,389	1,433,222	38,816,047
2018	1,548	437,005,166	282,303	1,428,620	36,187,577
2019	1,531	448,059,984	292,658	1,473,351	36,311,052
2020	1,509	455,137,413	301,615	1,431,263	31,865,776

Note: FTS: Full Time Sample.

Table A4: FTS Sample 1
Summary statistics: Equity capital by year (1990–2020)
($000 omitted)

Year	N	Sum	Mean	Std	Min	Max
1990	1,389	158,546,901	114,144,637	592,570,592	8,338	17,889,083
1991	1,444	173,829,187	120,380,324	630,474,049	34,590	19,721,100
1992	1,461	177,377,546	121,408,314	606,605,978	58,072	18,751,399
1993	1,488	199,444,021	134,034,961	688,739,668	46,887	21,269,733
1994	1,503	208,409,100	138,662,076	692,173,811	67,200	21,143,916
1995	1,560	251,900,679	161,474,794	850,780,971	61,413	25,119,972
1996	1,624	286,667,232	176,519,232	1,008,369,557	3,312	30,053,793
1997	1,667	355,097,194	213,015,714	1,300,376,162	118,382	37,608,321
1998	1,677	386,753,274	230,622,108	1,415,157,576	251,354	41,766,158
1999	1,663	389,497,488	234,213,764	1,486,770,786	25,092	45,762,499
2000	1,639	362,829,587	221,372,536	1,405,263,364	10,794	43,690,982
2001	1,636	340,892,568	208,369,541	1,192,500,533	204,582	37,989,955
2002	1,615	334,593,011	207,178,336	1,086,254,632	64,294	31,600,584
2003	1,595	403,289,846	252,846,298	1,394,916,364	165,529	39,980,587
2004	1,596	454,269,314	284,629,896	1,601,547,772	773	461,44,210
2005	1,578	496,797,400	314,827,250	1,731,283,163	107237	50,187,253
2006	1,589	568,217,330	357,594,293	2,030,838,987	246,477	58,034,267
2007	1,604	612,255,763	381,705,588	2,168,536,606	345,906	63,577,269
2008	1,626	549,738,270	338,092,417	1,818,159,437	65,916	53,273,951
2009	1,613	611,689,263	379,2245,90	2,087,473,237	161,832	58,180,271
2010	1,596	657,498,627	411,966,558	2,592,473,119	265,602	68,437,054
2011	1,609	655,961,572	407,682,767	2,595,877,200	67,595	70,155,427
2012	1,612	697,411,162	432,637,198	2,849,514,459	15,406	78,861,514
2013	1,604	761,466,077	474,729,475	3,364,615,160	1,250	97,226,051
2014	1,574	780,443,239	495,834,332	3,426,861,007	1,153	93,997,651
2015	1,632	793,579,778	486,262,119	3,338,676,082	1,853	89,828,618
2016	1,609	827,568,694	514,337,287	3,649,783,392	77,634	101,285,906
2017	1,591	888,790,475	558,636,377	4,327,584,269	77,103	128,562,565
2018	1,548	880,890,562	569,050,751	4,327,085,993	186,575	122,471,086
2019	1,531	1,013,362,400	661,895,759	5,522,467,069	256,147	167,718,678
2020	1,509	1,085,524,198	719,366,599	6,140,746,891	167,443	187,762,294

Note: NFTS: Non Full Time Sample.

Table A5: FTS Sample 1
Distribution of net losses
($000 omitted)

Year	L_{t-9}	L_{t-8}	L_{t-7}	…	L_{t-2}	L_{t-1}	L_t	$\bar{L}$	$\hat{\sigma}$
1990	74,414,479	83,740,459	92,568,162	…	146,335,428	163,586,889	171,374,407	120,997,141	32,893,055.73
1991	83,456,062	92,599,368	106,045,142	…	162,886,621	169,301,376	176,052,958	130,724,318	32,217,730.24
1992	92,647,718	106,321,361	116,924,431	…	167,742,711	172,767,662	190,313,741	140,897,569	32,042,208.09
1993	106,624,102	117,284,584	120,830,527	…	170,884,525	187,390,339	181,856,782	148,902,402	28,846,066.45
1994	117,281,706	120,793,434	130,361,714	…	183,781,628	178,171,262	198,108,492	157,097,641	27,643,200.16
1995	121,330,023	130,267,248	143,809,787	…	177,237,140	197,522,574	195,420,453	164,868,005	25,900,783.31
1996	130,295,151	143,751,177	162,636,588	…	195,939,244	193,721,909	206,486,353	172,613,282	23,588,685.04
1997	142,545,496	161,646,113	166,091,936	…	191,438,008	204,564,120	201,252,911	178,221,256	19,675,467.40
1998	161,030,019	165,514,511	166,444,345	…	202,457,275	198,605,104	210,282,050	183,617,601	17,287,699.41
1999	164,989,834	166,273,270	178,394,896	…	198,414,779	210,943,074	216,479,256	188,953,956	18,295,004.65
2000	161,832,267	173,916,592	166,783,739	…	211,492,329	217,357,930	229,485,981	192,871,403	22,179,899.89
2001	170,383,410	164,129,958	185,343,855	…	220,814,423	233,343,042	256,830,748	202,341,328	29,145,364.27
2002	163,329,224	185,170,740	183,094,367	…	239,890,904	259,079,558	257,085,229	213,964,782	32,445,457.63
2003	183,262,364	181,666,295	195,65,1689	…	258,870,910	248,895,008	268,3442,00	222,000,642	31,991,873.91
2004	181,247,887	195,657,075	195,804,754	…	249,198,170	255,045,500	279,0725,93	231,160,175	32,415,738.51
2005	195,532,170	196,212,105	218,380,744	…	253,15,6354	266,200,435	301,2747,67	242,564,434	32,958,429.10
2006	194,896,671	217,107,302	229,258,222	…	260,102,398	288,520,118	285,720,875	249,191,819	28,869,336.95
2007	218,297,148	230,639,185	249,137,841	…	284,400,126	276,740,621	300,912,718	258,96,9515	24,580,575.94
2008	230,948,463	250,138,181	265,457,113	…	272,743,918	296,362,660	345,168,298	270,728,397	32,043,915.65
2009	249,301,425	264,911,266	252,434,049	…	291,826,043	339,738,585	316,309,049	277,301,757	30,573,897.58
2010	260,192,930	248,596,078	246,233,069	…	334,570,606	308,943,902	315,294,344	279,551,041	31,069,883.52
2011	254,896,045	252,473,633	256,596,353	…	306,270,626	312,770,589	351,449,025	290,960,149	34,928,416.37
2012	251,604,283	256,078,212	277,317,579	…	311,243,831	344,377,981	341,523,488	298,102,377	34,861,517.93
2013	256,171,787	277,855,414	263,854,070	…	344,027,261	332,653,260	327,588,106	304,544,226	30,868,455.06
2014	275,473,365	261,702,820	281,133,928	…	330,284,145	319,968,627	343,463,626	309,745,108	28,175,246.69
2015	262,810,797	283,430,758	324,298,418		321,953,494	339,536,074	357,822,910	319,299,665	28,552,556.11
2016	281,248,062	322,324,631	301,047,232		338,865,315	353,057,645	381,780,711	329,007,328	28,103,904.50
2017	320,898,234	299,501,944	302,693,023		352,497,619	376,839,754	419,052,497	341,203,579	35,533,124.90
2018	299,397,701	305,594,617	339,504,878		376,006,361	411,181,111	437,005,166	351,538,030	44,529,762.03
2019	303,558,374	337,364,597	326,187,667		408,728,464	429,581,444	448,059,984	363,597,133	49,743,873.74
2020	336,081,747	324,629,134	314,403,406		427,517,806	443,105,545	455,137,413	376,422,733	52,513,340.78

Note: Sum of the observed losses of company i incurred in year $t–9$ up to t ($L_{t-9}, \dots L_t$). $\bar{L}$ and $\hat{\sigma}$ of losses for the industry by year (1990–2020).

Table A6: ($\hat{\sigma}_i$) FTS Sample 1
($000 omitted)

Year	N	Mean	Std	Min	Max
1990	1,389	28,896.89	153,266.69	1.90	4,117,902.16
1991	1,444	28,285.71	153,603.01	1.52	4,175,781.98
1992	1,461	29,001.89	163,666.97	1.32	4,184,769.02
1993	1,488	28,271.59	155,126.49	0.70	4,047,432.60
1994	1,503	28,031.22	153,805.97	6.11	4,160,714.72
1995	1,560	27,289.46	143,088.30	5.86	4,038,217.10
1996	1,624	26,691.71	126,921.89	7.04	3,531,777.62
1997	1,667	25,357.20	107,760.08	6.26	2,859,433.91
1998	1,677	24,385.01	94,739.98	6.07	2,403,336.98
1999	1,663	24,602.95	91,232.49	2.53	2,056,463.79
2000	1,639	26,284.24	97,870.52	3.52	2,142,909.44
2001	1,636	29,277.32	110,785.74	0.97	2,408,613.36
2002	1,615	31,747.85	121,748.78	0.32	2,825,926.51
2003	1,595	34,310.36	126,525.62	0.32	2,826,442.64
2004	1,596	36,925.36	131,901.68	5.08	2,847,132.67
2005	1,578	39,687.63	146,392.88	0.67	3,301,741.99
2006	1,589	39,690.58	140,673.87	0.67	2,822,807.25
2007	1,604	39,863.78	139,858.88	0.67	2,595,686.90
2008	1,626	44,203.38	153,565.17	5.95	2,339,542.42
2009	1,613	43,552.17	151,460.50	1.03	1,957,636.38
2010	1,596	41,513.42	145,298.42	1.16	2,006,493.32
2011	1,609	43,143.13	153,674.77	0.67	2,483,517.16
2012	1,612	42,065.40	147,767.89	0.67	2,369,475.80
2013	1,604	40,145.20	140,878.39	5.33	2,261,733.09
2014	1,574	39,122.05	154,097.32	0.57	3,419,126.79
2015	1,632	39,291.84	173,303.39	0.95	4,486,420.20
2016	1,609	40,432.54	201,018.55	0.47	5,194,632.04
2017	1,591	44522.55	226,404.97	0.32	6,170,229.88
2018	1,548	49,860.80	241,902.79	0.32	6,760,598.56
2019	1,531	51,999.15	249,680.68	0.32	7,041,168.30
2020	1,509	53,481.45	243,722.37	0.32	6,800,905.57

Note: Standard deviation of losses for a company by year (1990–2020).

Table A7: ($\hat{\rho}_i$) FTS Sample 1

Year	N	Mean	Std	Min	Max
1990	1,389	0.5996	0.4984	-0.9138	0.9967
1991	1,444	0.5720	0.5153	-0.9281	0.9970
1992	1,461	0.5505	0.5176	-0.9385	0.9974
1993	1,488	0.5172	0.5262	-0.9816	0.9924
1994	1,503	0.5085	0.5442	-0.9721	0.9919
1995	1,560	0.5034	0.5490	-0.9712	0.9908
1996	1,624	0.4866	0.5569	-0.9303	0.9853
1997	1,667	0.4390	0.5859	-0.9579	0.9862
1998	1,677	0.4151	0.5987	-0.9718	0.9836
1999	1,663	0.4071	0.5952	-0.9523	0.9823
2000	1,639	0.4143	0.5882	-0.9399	0.9909
2001	1,636	0.4505	0.5600	-0.9416	0.9909
2002	1,615	0.4629	0.5558	-0.9536	0.9960
2003	1,595	0.4619	0.5492	-0.9699	0.9925
2004	1,596	0.4681	0.5327	-0.9564	0.9900
2005	1,578	0.4606	0.5235	-0.9447	0.9922
2006	1,589	0.4277	0.5247	-0.9100	0.9830
2007	1,604	0.3964	0.5265	-0.9245	0.9765
2008	1,626	0.3975	0.5087	-0.8969	0.9773
2009	1,613	0.3633	0.5344	-0.8786	0.9757
2010	1,596	0.3683	0.5427	-0.9556	0.9765
2011	1,609	0.4105	0.5590	-0.9363	0.9895
2012	1,612	0.4181	0.5593	-0.9606	0.9839
2013	1,604	0.3838	0.5450	-0.9173	0.9677
2014	1,574	0.4039	0.5000	-0.8938	0.9644
2015	1,632	0.3974	0.4970	-0.8992	0.9740
2016	1,609	0.3875	0.5015	-0.9024	0.9801
2017	1,591	0.4329	0.5129	-0.9589	0.9813
2018	1,548	0.4767	0.5218	-0.9776	0.9832
2019	1,531	0.4854	0.5263	-0.9830	0.9926
2020	1,509	0.4668	0.5402	-0.9929	0.9921

Note: Correlation coefficient between company i's losses and the industry losses by year (1990–2020).

Table A8: ($det\hat{\sigma}_i$) FTS Sample 1
($000 omitted)

Year	N	Mean	Std	Min	Max
1990	1,389	10,725.43	36,358.13	1.18	707,207.31
1991	1,444	10,644.01	33,107.90	1.23	510,089.40
1992	1,461	12,054.57	46,534.36	0.94	1,131,199.48
1993	1,488	13,233.55	51,719.14	0.57	1,258,690.85
1994	1,503	13,418.34	51,782.24	5.80	1,255,141.69
1995	1,560	13,292.76	54,485.09	5.27	1,357,146.75
1996	1,624	13,189.24	53,465.60	6.00	1,372,895.41
1997	1,667	13,110.83	56,459.72	5.77	1,464,568.60
1998	1,677	13,343.78	55,477.03	5.22	13,55,153.35
1999	1,663	13,724.02	57,107.97	2.44	1,325,129.18
2000	1,639	14,704.94	58,948.87	3.38	1,208,974.12
2001	1,636	16,236.37	65,147.14	0.77	1,413,865.68
2002	1,615	17,404.10	69,619.16	0.29	1,699,290.42
2003	1,595	19,254.78	73,631.27	0.27	1,641,447.78
2004	1,596	20,276.28	72,043.03	4.41	1,046,982.82
2005	1,578	21,568.18	76,328.53	0.50	1,335,272.97
2006	1,589	21,587.37	77,857.41	0.50	1,353,014.05
2007	1,604	22,025.38	82,061.92	0.50	1,579,697.25
2008	1,626	25,487.28	95,739.56	4.54	1,714,096.76
2009	1,613	26,191.50	96,580.23	0.93	1,597,155.77
2010	1,596	26,020.38	96,160.44	1.11	1,651,997.08
2011	1,609	25,762.17	92,713.73	0.64	1,776,210.43
2012	1,612	24,949.79	90,806.59	0.62	1,689,905.59
2013	1,604	25,309.53	96,704.64	4.69	1,863,772.96
2014	1,574	25,818.21	107,436.31	0.54	2,0408,39.11
2015	1,632	24,632.51	97,704.53	0.81	1,878,516.44
2016	1,609	23,644.81	99,665.42	0.47	2,089,036.67
2017	1,591	24,386.03	98,191.02	0.30	1,948,005.82
2018	1,548	25,392.86	91,481.23	0.31	1,606,395.66
2019	1,531	26,424.46	93,703.10	0.32	1,345,644.65
2020	1,509	28,043.87	106,060.33	0.32	1,974,576.45

Note: Detrended standard deviation of losses for a company by year (1990–2020).

Table A9: ($det\hat{\rho}_i$) FTS Sample 1

Year	N	Mean	Std	Min	Max
1990	1,389	0.2020	0.4308	-0.9210	0.9654
1991	1,444	0.1696	0.3666	-0.9140	0.9497
1992	1,461	0.1576	0.3550	-0.8516	0.8855
1993	1,488	0.0822	0.4071	-0.8278	0.9336
1994	1,503	0.1064	0.3829	-0.8121	0.8649
1995	1,560	0.0785	0.4507	-0.9411	0.8798
1996	1,624	0.1116	0.3703	-0.7928	0.8750
1997	1,667	0.1257	0.2949	-0.8784	0.8786
1998	1,677	0.1460	0.2634	-0.7633	0.8850
1999	1,663	0.1169	0.2648	-0.8019	0.8629
2000	1,639	0.1267	0.3323	-0.8331	0.8939
2001	1,636	0.1898	0.4559	-0.8794	0.9336
2002	1,615	0.1400	0.3675	-0.8739	0.9405
2003	1,595	0.1084	0.3746	-0.8803	0.9450
2004	1,596	0.0124	0.4518	-0.8877	0.9185
2005	1,578	0.0545	0.4367	-0.9248	0.9380
2006	1,589	0.0308	0.4824	-0.9093	0.9160
2007	1,604	0.0891	0.4211	-0.9270	0.9461
2008	1,626	0.1760	0.5158	-0.8990	0.9782
2009	1,613	0.1781	0.4872	-0.8561	0.9492
2010	1,596	0.1727	0.4424	-0.8937	0.9414
2011	1,609	0.2120	0.3531	-0.8162	0.9433
2012	1,612	0.1746	0.3142	-0.8069	0.8978
2013	1,604	0.1481	0.3848	-0.8110	0.9172
2014	1,574	0.1621	0.3728	-0.7425	0.8999
2015	1,632	0.1571	0.4035	-0.8010	0.9262
2016	1,609	0.1924	0.3552	-0.7835	0.9462
2017	1,591	0.2791	0.4496	-0.8749	0.9703
2018	1,548	0.2522	0.5055	-0.9404	0.9636
2019	1,531	0.2670	0.5085	-0.9369	0.9790
2020	1,509	0.2419	0.4857	-0.9657	0.9845

Note: Detrended correlation coefficient between company i's losses and the industry losses by year (1990–2020).

Table A10a: FTS Sample 1
Tobit censored (Lb=0) model
Standard deviations: Net losses incurred 1997

Variable	Companies Raw	Companies Detrended	Group Raw	Group Detrended
Intercept	0.1490 7.69	-0.1919 -11.29	0.2099 4.57	0.1017 4.67
Ln (equity capital)	0.0231 10.19	0.0120 10.00	0.0403 7.34	0.0184 7.07
Ln (net losses incurred)	0.0039 2.16	0.0016 1.66	0.0016 0.35	0.0010 0.46
Short / Asset	0.0837 4.97	0.0431 4.83	0.1362 4.05	0.0649 4.07
Liquid asset / Asset	-0.0389 -1.79	-0.0237 -2.06	-0.0423 -0.81	-0.0242 -0.98
Sigma	0.0975 57.74	0.0515 57.73	0.1622 41.88	0.0769 41.88
Log likelihood	1,515	2,578	351	1,006
AIC	-3,019	-5,144	-690	-1,999
No. of observations	1,667	1,667	877	877

Note: Short = Cash + cash equivalent and short-term investment; Liquid asset = bond + stock + short. Lb is for lower bond. The dependent variable is the standard deviation of net losses incurred. For each variable, we report the regression coefficient and the *t*-ratio.

Table A10b: FTS Sample 1
Tobit censored (Lb=0) model
Standard deviations: Net losses incurred 2005

Variable	Companies Raw	Companies Detrended	Group Raw	Group Detrended
Intercept	0.1952	-0.3165	0.3666	0.1891
	9.39	-14.58	6.43	6.39
Ln (equity capital)	0.0353	0.0194	0.0629	0.0334
	11.62	12.22	8.05	8.26
Ln (net losses incurred)	0.0058	0.0016	0.0048	0.0005
	2.37	1.27	0.72	0.14
Short / Asset	0.1117	0.0501	0.2186	0.1084
	5.28	4.52	4.35	4.16
Liquid asset / Asset	-0.0401	-0.0302	-0.1309	-0.0729
	-1.61	-2.31	-1.91	-2.05
Sigma	0.1270	0.0665	0.2356	0.1222
	56.17	56.17	41.30	41.30
Log likelihood	1,017	2,038	23	583
AIC	-2,022	-4,065	-33	-1,153
No. of observations	1,578	1,578	853	853

Note: Short = Cash + cash equivalent and short-term investment; Liquid asset = bond + stock + short. Lb is for lower bond. The dependent variable is the standard deviation of net losses incurred. For each variable, we report the regression coefficient and the *t*-ratio.

Table A10c: FTS Sample 1
Tobit censored (Lb=0) model
Standard deviations: Net losses incurred 2014

Variable	Companies Raw	Companies Detrended	Group Raw	Group Detrended
Intercept	0.1687 8.32	-0.4161 -13.74	0.3041 5.66	0.1896 5.80
Ln (equity capital)	0.0318 10.03	0.0219 9.79	0.0558 6.89	0.0333 6.76
Ln (net losses incurred)	0.0081 2.99	0.0045 2.31	0.0087 1.17	0.0048 1.07
Short / Asset	0.1147 4.65	0.0745 4.27	0.2026 3.70	0.1115 3.35
Liquid asset / Asset	-0.0033 -0.95	-0.0140 -0.80	-0.0842 -1.29	-0.0584 -1.47
Sigma	0.1361 57.74	0.0962 56.10	0.2437 41.08	0.1484 41.08
Log likelihood	-1,800	1,451	-6	413
AIC	906	-2,890	24	-813
No. of observations	1,574	1,574	844	844

Note: Short = Cash + cash equivalent and short-term investment; Liquid asset = bond + stock + short. Lb is for lower bond. The dependent variable is the standard deviation of net losses incurred. For each variable, we report the regression coefficient and the *t*-ratio.

Table A10d: FTS Sample 1
Tobit censored (Lb=0) model
Standard deviations: Net losses incurred 2020

Variable	Companies Raw	Companies Detrended	Group Raw	Group Detrended
Intercept	0.2520	-0.4745	0.4290	0.2014
	8.12	-15.72	5.26	7.49
Ln (equity capital)	0.0548	0.0286	0.1012	0.0439
	9.62	11.95	6.94	9.14
Ln (net losses incurred)	0.0035	0.0005	-0.0015	-0.0016
	0.75	0.24	-0.12	-0.40
Short / Asset	0.1366	0.0664	0.3182	0.1191
	3.61	4.19	3.47	3.94
Liquid asset / Asset	-0.0729	-0.0337	-0.1428	-0.0771
	-1.93	-2.13	-1.44	-2.36
Sigma	0.2187	0.0917	0.4068	0.1340
	54.93	54.93	41.01	41.01
Log likelihood	152	1,465	-437	497
AIC	-293	-2,917	886	-981
No. of observations	1,509	1,509	841	841

Note: Short = Cash + cash equivalent and short-term investment; Liquid asset = bond + stock + short. Lb is for lower bond.The dependent variable is the standard deviation of net losses incurred. For each variable, we report the regression coefficient and the *t*-ratio.

Table A11a: FTS Sample 1
Tobit censored (Lb=-1 Ub=1) model
Correlation coefficient: Net losses incurred 1997

Variable	Companies Raw	Companies Detrended	Group Raw	Group Detrended
Intercept	0.6155 4.74	-0.2556 -2.33	0.6311 3.95	0.2908 2.85
Ln (equity capital)	-0.1854 -13.14	0.0190 2.48	-0.1413 -7.83	0.0136 1.18
Ln (net losses incurred)	0.2038 15.94	-0.0043 -0.63	0.1747 10.61	0.0057 0.54
Short / Asset	-0.2251 -2.42	-0.1419 -2.81	-0.2748 -2.83	-0.1130 -1.82
Total liability / Asset	-0.4826 -5.45	0.0834 -1.76	-0.3800 -3.53	-0.0273 -1.83
Liquid asset / Asset	0.4003 3.31	0.0761 1.16	0.4446 2.93	-0.0809 -0.83
Sigma	0.5370 57.74	0.2909 57.74	0.4651 41.88	0.2976 41.78
Log likelihood	-1,329	-307	-573	-181
AIC	2,672	628	1,160	376
No. of observations	1,667	1,667	877	877

Note: Short = Cash + cash equivalent and short-term investment. Liquid asset = bond + stock + short. Lb and Ub are for lower bond and upper bond. The dependent variable is the correlation coefficient of net losses incurred. For each variable, we report the regression coefficient and the *t*-ratio.

Table A11b: FTS Sample 1
Tobit censored (Lb=-1 Ub=1) model
Correlation coefficient: Net losses incurred 2005

Variable	Companies Raw	Companies Detrended	Group Raw	Group Detrended
Intercept	0.6000 5.61	-0.8631 -5.11	0.5953 4.18	0.1979 1.41
Ln (equity capital)	-0.1516 -12.32	0.0446 3.83	-0.1308 -8.24	0.0426 2.72
Ln (net losses incurred)	0.1982 17.61	-0.0054 -0.51	0.1689 11.22	-0.0206 -0.80
Short / Asset	-0.0315 -0.42	-0.0528 -0.74	-0.1854 -2.08	0.0206 0.23
Total liability / Asset	-0.1839 -2.15	0.1523 1.88	-0.1963 -1.79	0.0301 0.28
Liquid asset / Asset	0.3515 3.84	0.1314 1.52	0.3753 3.00	-0.1618 -1.31
Sigma	0.4529 57.74	0.4283 56.18	0.4168 41.30	0.4101 41.30
Log likelihood	-989	-901	-464	-542
AIC	1,992	1,816	942	917
No. of observations	1,578	1,578	853	853

Note: Short = Cash + cash equivalent and short-term investment. Liquid asset = bond + stock + short. Lb and Ub are for lower bond and upper bond. The dependent variable is the correlation coefficient of net losses incurred. For each variable, we report the regression coefficient and the *t*-ratio.

Table A11c: FTS Sample 1
Tobit censored (Lb=-1 Ub=1) model
Correlation coefficient: Net losses incurred 2014

Variable	Companies Raw	Companies Detrended	Group Raw	Group Detrended
Intercept	0.7600 6.66	-0.3682 -2.53	0.8444 5.30	0.5688 4.62
Ln (equity capital)	-0.0953 -7.78	0.0301 3.11	-0.0875 -4.96	0.0108 0.79
Ln (net losses incurred)	0.1344 11.59	0.0074 0.81	0.1314 7.60	0.0292 2.19
Short / Asset	-0.4214 -5.07	-0.1676 -2.55	-0.3617 -3.60	-0.0359 -0.46
Total liability / Asset	-0.1707 -1.82	0.0085 0.12	-0.3479 -2.68	-0.1818 -1.81
Liquid asset / Asset	0.0359 0.39	-0.0816 -1.13	0.0416 0.32	-0.1818 -1.81
Sigma	0.4587 56.11	0.3621 56.11	0.4462 41.08	0.3444 41.08
Log likelihood	-1,007	-635	-516	-298
AIC	2,027	1,283	1,047	610
No. of observations	1,574	1,574	844	844

Note: Short = Cash + cash equivalent and short-term investment. Liquid asset = bond + stock + short. Lb and Ub are for lower bond and upper bond. The dependent variable is the correlation coefficient of net losses incurred. For each variable, we report the regression coefficient and the *t*-ratio.

Table A11d: FTS Sample 1
Tobit censored (Lb=-1 Ub=1) model
Correlation coefficient: Net losses incurred 2020

Variable	Companies Raw	Companies Detrended	Group Raw	Group Detrended
Intercept	0.8806 7.36	-0.2092 -1.04	0.9784 6.06	0.5976 4.14
Ln (equity capital)	-0.0933 -6.18	-0.0160 -1.12	-0.1059 -5.21	-0.0258 -1.42
Ln (net losses incurred)	0.14.91 10.85	0.0670 5.19	0.1676 8.99	0.0840 5.04
Short / Asset	0.0093 0.11	-0.1831 -2.28	-0.0451 -0.40	-0.0054 -0.05
Total liability / Asset	-0.0757 -0.75	-0.0529 -0.56	-0.3499 -2.64	-0.4080 -3.45
Liquid asset / Asset	-0.0941 -1.00	0.1362 1.55	-0.0165 -0.13	0.0387 0.33
Sigma	0.4942 54.92	0.2600 57.11	0.4936 41.01	0.4413 41.01
Log likelihood	-1,077	-984	-600	-505
AIC	2,168	1,983	1,213	1,025
No. of observations	1,508	1,508	841	841

Note: Short = Cash + cash equivalent and short-term investment. Liquid asset = bond + stock + short. Lb and Ub are for lower bond and upper bond. The dependent variable is the correlation coefficient of net losses incurred. For each variable, we report the regression coefficient and the *t*-ratio.

Table A12: ($\hat{\sigma}_i$) NFTS company Sample 1
Raw parameter estimates
($000 omitted)

Year	N	Mean	St	Min	Max
1990	2,214	38,262.78	122,647.24	1.9002924	4117,902.16
1991	2,241	37,257.02	124,521.22	1.5238839	4175,781.98
1992	2,255	38,491.61	133,002.82	1.3165612	4184,769.02
1993	2,252	36,727.27	127,275.28	0.6992059	404,7432.60
1994	2,267	36,419.91	126,388.33	6.1110101	416,0714.72
1995	2,280	34,511.77	119,377.04	5.8585171	4038,217.10
1996	2,285	31,921.98	107,770.91	7.0364132	353,1777.62
1997	2,286	29,353.53	92,700.48	6.2618776	285,9433.91
1998	2,277	27,553.65	82,005.49	6.0745370	240,3336.98
1999	2,213	27,112.82	79,766.38	2.5298221	205,6463.79
2000	2,165	28,947.64	85,853.00	3.5213634	214,2909.44
2001	2,137	31,521.77	97,563.02	0.9660918	240,8613.36
2002	2,103	34,955.22	107,517.57	0.3162278	282,5926.51
2003	2,101	36,983.62	111,073.02	0.3162278	282,6442.64
2004	2,143	39,145.19	114,745.54	5.0782762	284,7132.67
2005	2,152	42,452.05	126,396.80	0.6749486	330,1741.99
2006	2,193	41,618.41	120,717.28	0.6749486	282,2807.25
2007	2,223	41,733.10	119,734.33	0.6749486	259,5686.90
2008	2,246	46,170.06	131,774.17	5.9451194	233,9542.42
2009	2,207	46,099.45	130,553.41	1.0327956	195,7636.38
2010	2,163	43,566.03	125,713.44	1.1595018	200,6493.32
2011	2,119	44,877.34	134,718.38	0.6749486	248,3517.16
2012	2,069	43,282.95	131,184.67	0.6749486	236,9475.80
2013	2,016	41,625.23	1265,49.29	5.3343749	226,1733.09
2014	1,923	41,562.38	14,125.61	0.5676462	341,9126.79
2015	1,953	42,465.51	159,136.71	0.9486833	448,6420.20
2016	1,911	45,077.36	185,334.98	0.4714045	519,4632.04
2017	1,864	49,273.18	210,090.70	0.3162278	617,0229.88
2018	1,825	55,019.29	223,799.95	0.3162278	676,0598.56
2019	1,805	56,922.55	230,947.71	0.3162278	704,1168.30
2020	1,787	58,114.23	224,898.94	0.3162278	680,0905.57

Note: Standard deviation of the net losses and loss expense incurred for a company by year (1990–2020). NFTS: Non Full Time Sample.

Table A13: ($\hat{\rho}_i$) NFTS company Sample 1
Raw parameter estimates

Year	N	Mean	Std	Min	Max
1990	2,214	0.5441727	0.4222848	-0.9137534	0.9967239
1991	2,241	0.5353007	0.4349050	-0.9280519	0.9969796
1992	2,255	0.5205230	0.4366218	-0.9384972	0.9974125
1993	2,252	0.4966674	0.4463094	-0.9815604	0.9937107
1994	2,267	0.4837493	0.4634369	-0.9721156	0.9920304
1995	2,280	0.4852563	0.4711936	-0.9712140	0.9908177
1996	2,285	0.4709582	0.4835533	-0.9302615	0.9933658
1997	2,286	0.4376478	0.5104966	-0.9579326	0.9890006
1998	2,277	0.4190612	0.5216771	-0.9717621	0.9836439
1999	2,213	0.4104522	0.5242314	-0.9523313	0.9822703
2000	2,165	0.4102226	0.5215430	-0.9398921	0.9909369
2001	2,137	0.4362449	0.5007022	-0.9416348	0.9929707
2002	2,103	0.4435981	0.4977894	-0.9536398	0.9975875
2003	2,101	0.4445977	0.4899440	-0.9698603	0.9924989
2004	2,143	0.4492404	0.4715302	-0.9564016	0.9900277
2005	2,152	0.4399406	0.4610354	-0.9446858	0.9922169
2006	2,193	0.4106590	0.4573220	-0.9099513	0.9829975
2007	2,223	0.3894431	0.4553844	-0.9245297	0.9764916
2008	2,246	0.3829737	0.4406763	-0.8968988	0.9772564
2009	2,207	0.3537403	0.4626468	-0.8785671	0.9756570
2010	2,163	0.3621326	0.4715820	-0.9556466	0.9764595
2011	2,119	0.3962341	0.4936443	-0.9363437	0.9894695
2012	2,069	0.4008681	0.5007567	-0.9605558	0.9839189
2013	2,016	0.3697069	0.4919099	-0.9172777	0.9676735
2014	1,923	0.3847622	0.4591986	-0.8938171	0.9644265
2015	1,953	0.3804337	0.4602265	-0.8991615	0.9740115
2016	1,911	0.3723453	0.4663885	-0.9023961	0.9801297
2017	1,864	0.4150154	0.4806087	-0.9589268	0.9812657
2018	1,825	0.4542618	0.4896486	-0.9775956	0.9831742
2019	1,805	0.4627841	0.4933521	-0.9830116	0.9925968
2020	1,787	0.4487483	0.5038403	-0.9929358	0.9920923

Note: Correlation coefficient between company i's losses and the industry losses by year (1990–2020). NFTS: Non Full Time Sample.

A re-examination of U.S. insurance market capacity to pay catastrophe losses

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11 May 2022

Online appendix

Online appendix OA1

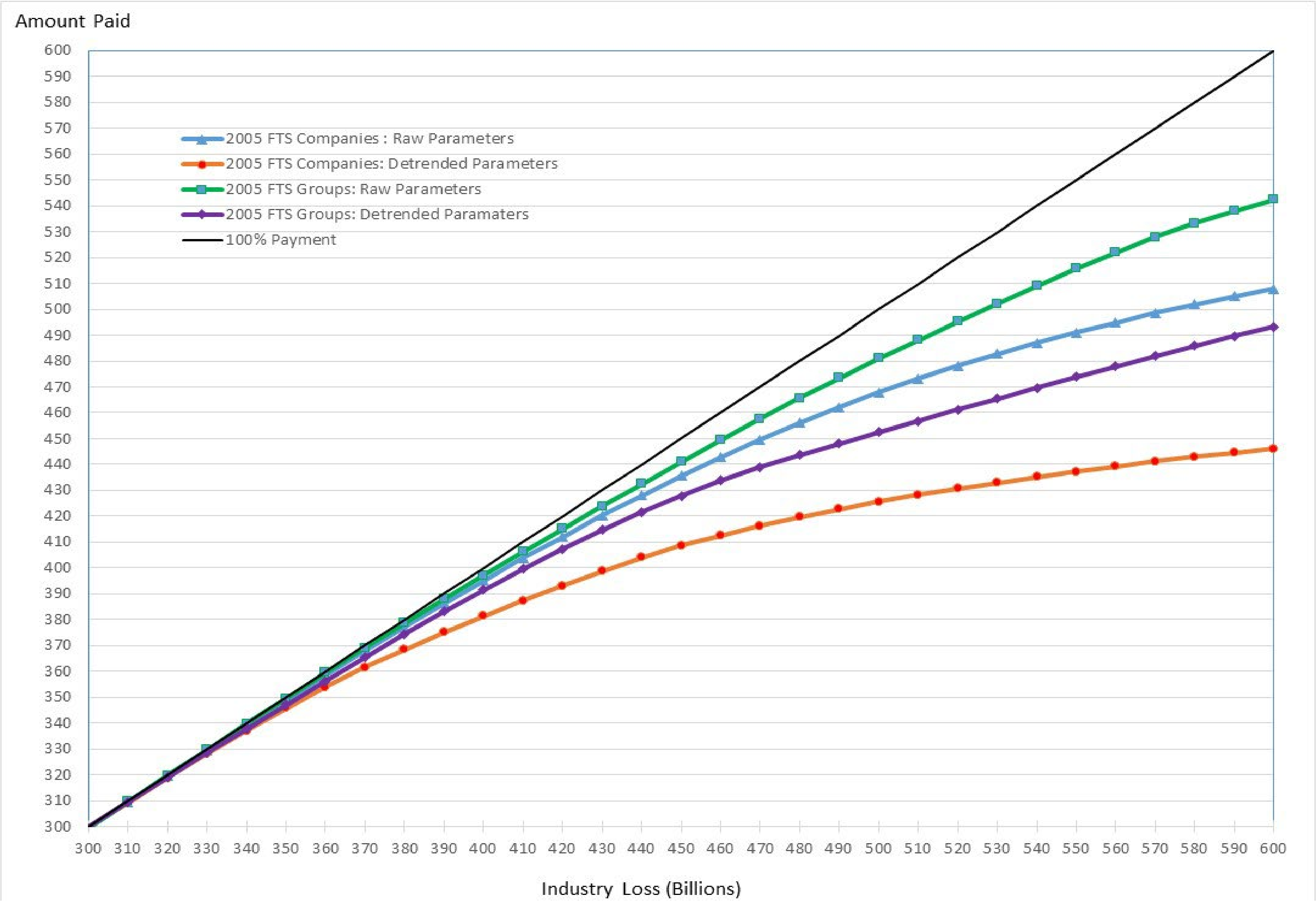

Figure O1: FTS Sample 1
Response functions insurance industry net loss, 2005

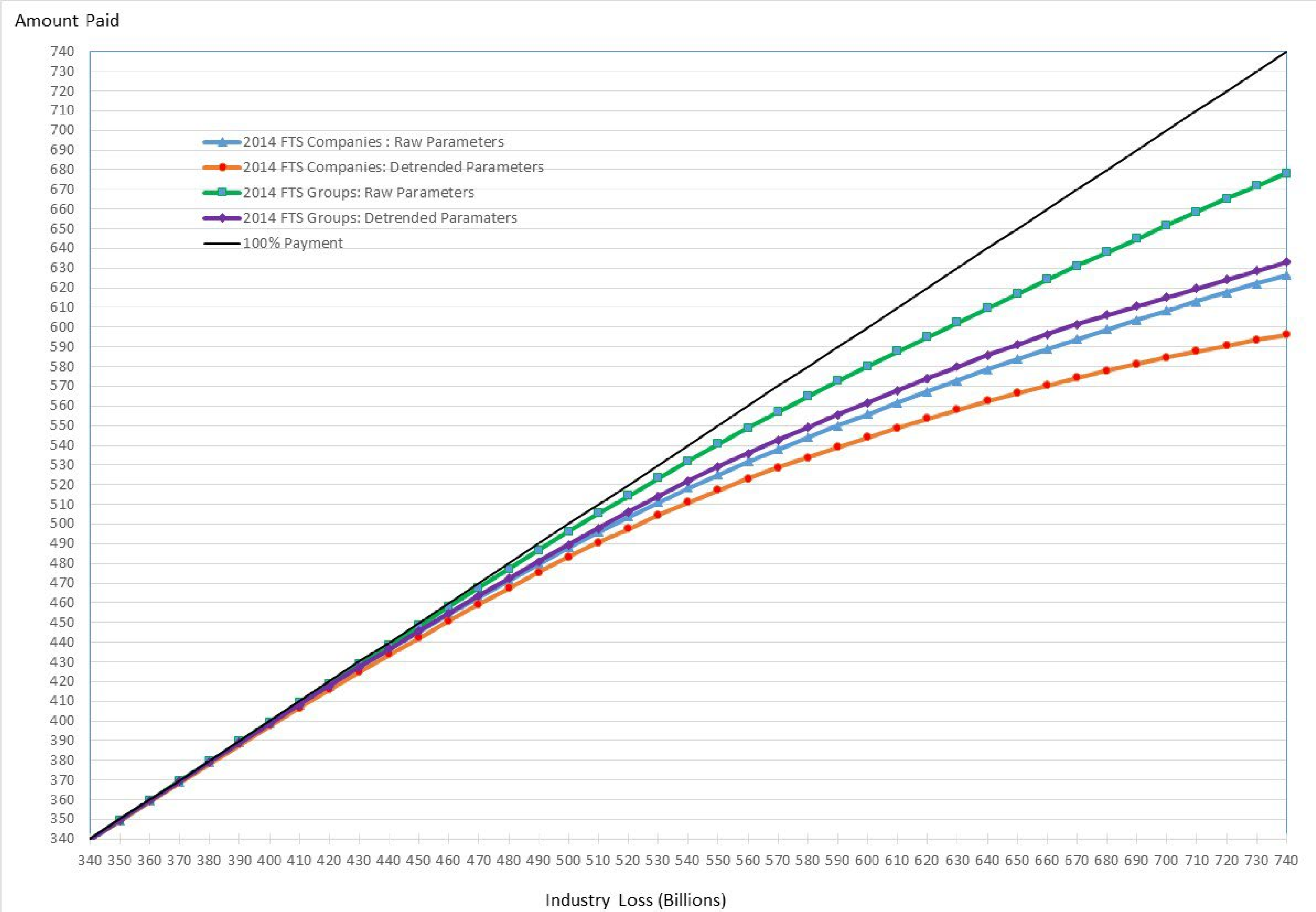

Figure O2: FTS Sample 1
Response functions insurance industry net loss, 2014

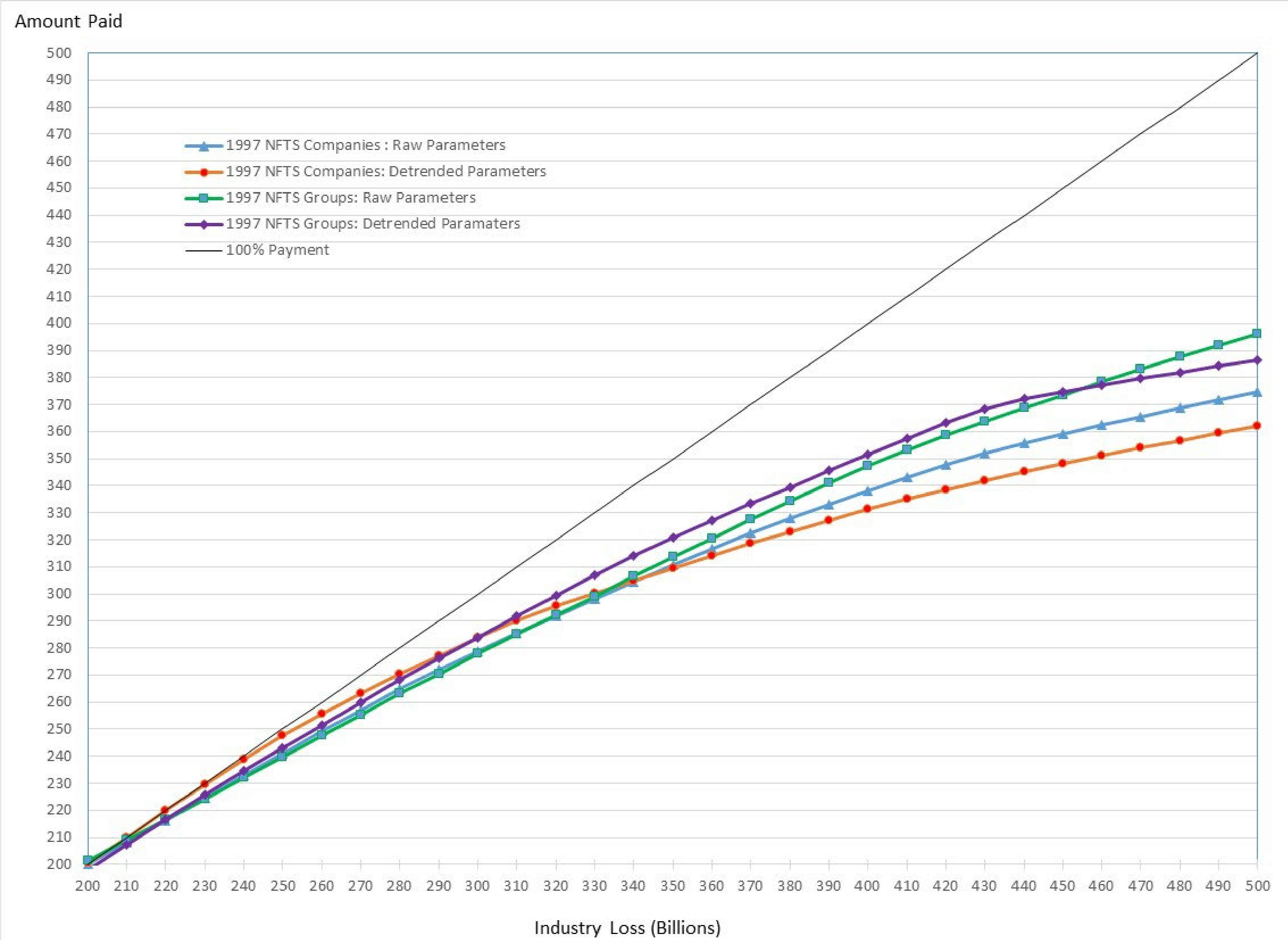

Figure O3: NFTS Sample 1
Response functions insurance industry net loss, 1997

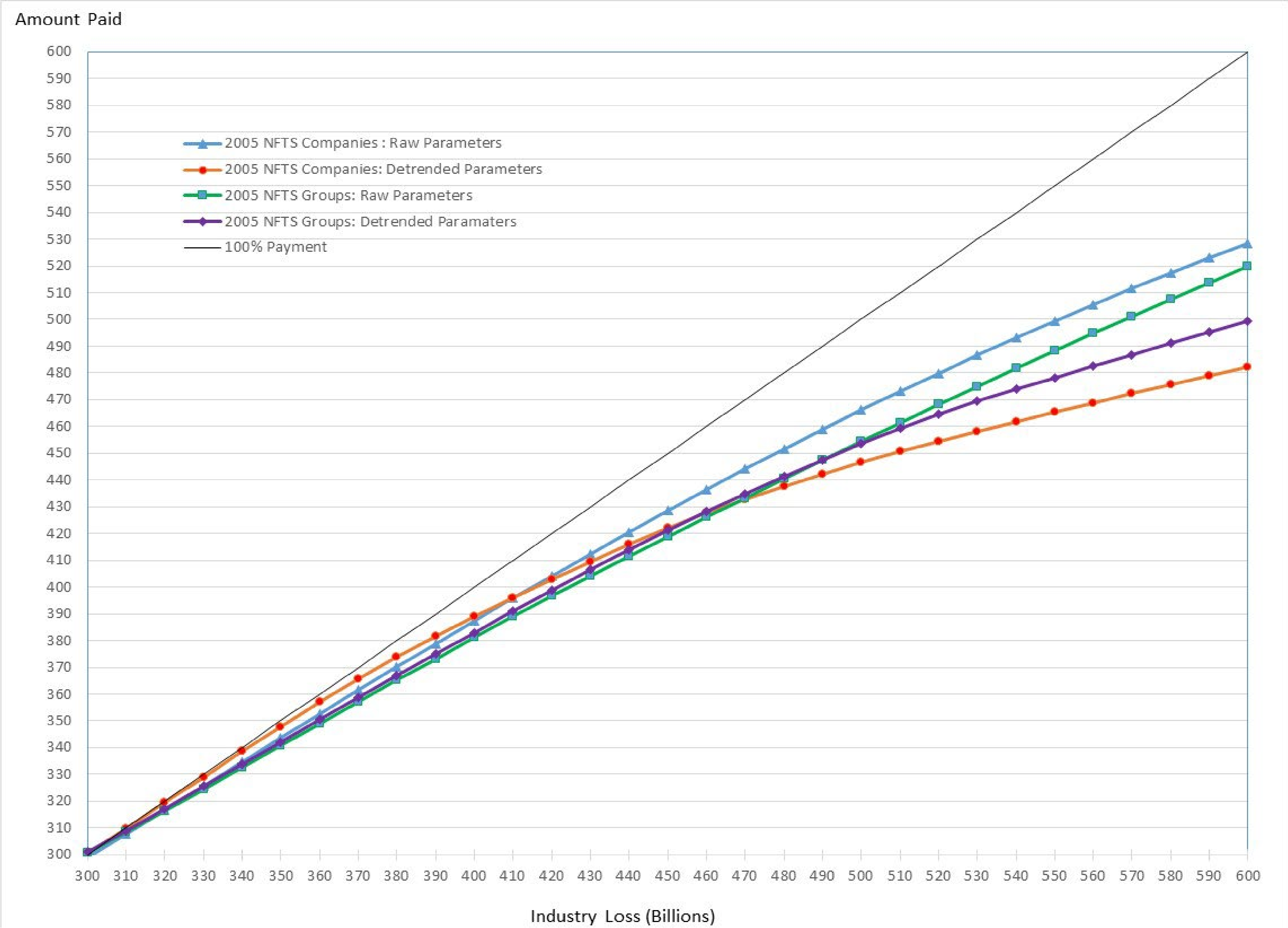

Figure O4: NFTS Sample 1
Response functions insurance industry net loss, 2005

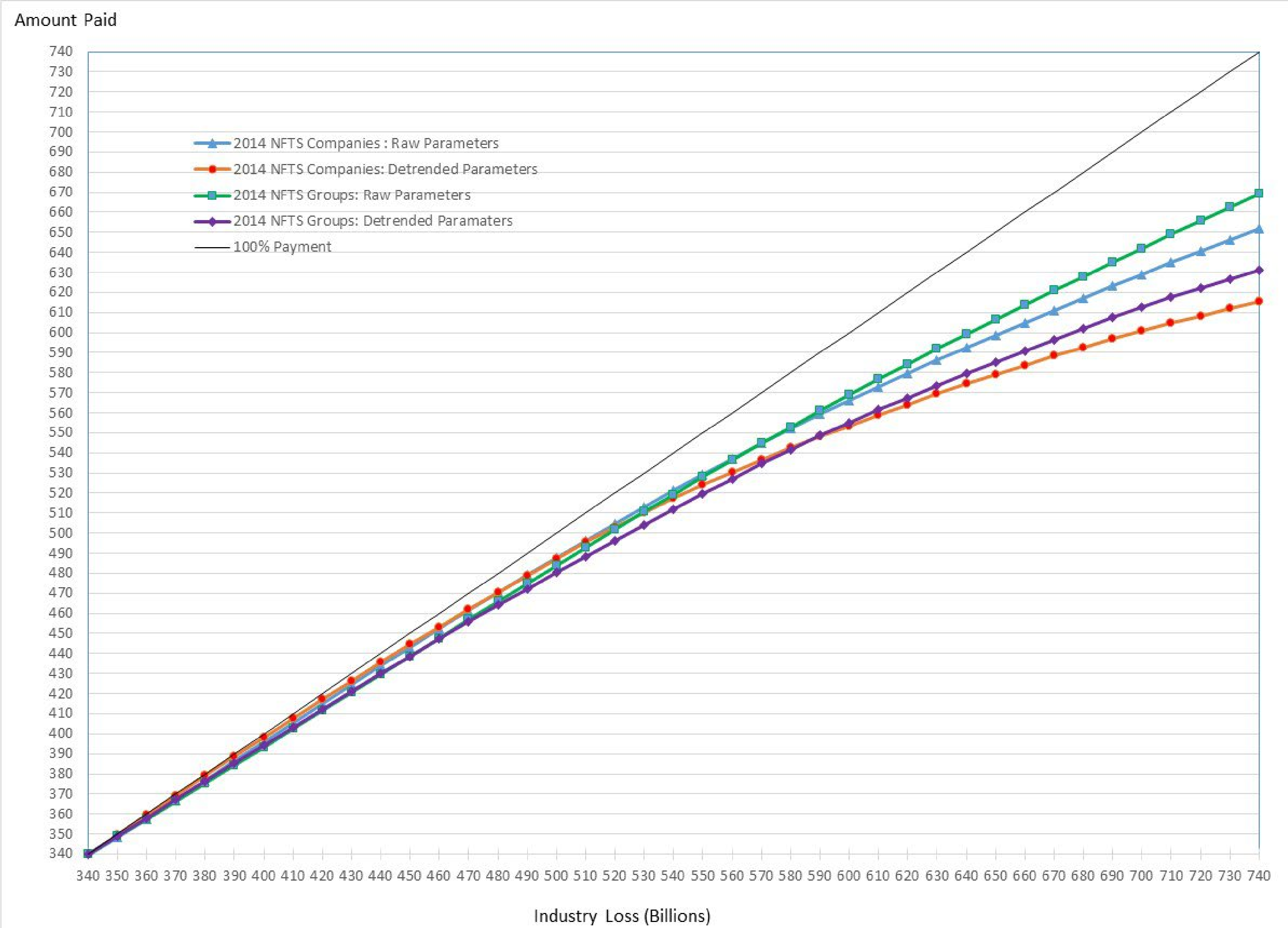

Figure O5: NFTS Sample 1
Response functions insurance industry net loss, 2014

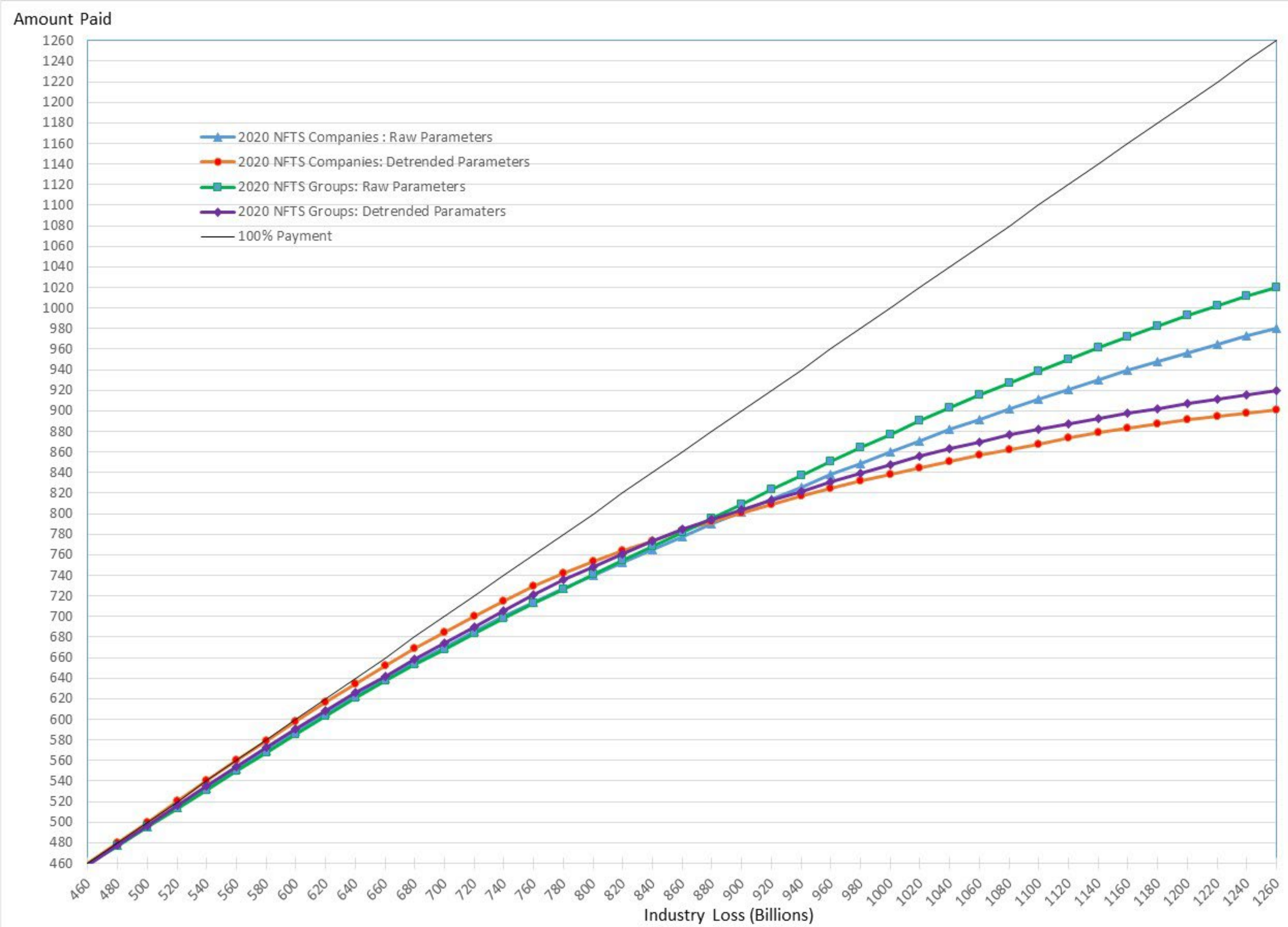

Figure O6: NFTS Sample 1
Response functions insurance industry net loss, 2020