SOCIAL INFLATION

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Abstract

I study the pricing of a novel source of aggregate risk to the insurance sector: shifts in insurers' loss distribution due to extreme jury verdicts and settlements, widely referred to as *social inflation* by insurers and regulators. A hedonic model shows that jury verdicts for accidents with identical characteristics have increased persistently since 2015, which insurers attribute to evolving social norms and legal tactics. Insurers face not only higher expected losses but also heightened uncertainty, due to both higher loss variability and uncertainty about loss distribution parameters. I then study the insurers' price response to social inflation, focusing on the auto insurance market. Leveraging within insurer-year variation across product lines and across geography, I find that social inflation accounts for nearly two thirds of the annual price increase since 2018. A model shows that this large price response includes a risk compensation due to the interaction of financial frictions with uncertainty in the loss distribution. Consistent with risk compensation in insurers' price response, I find (i) bigger hikes for more constrained insurers, (ii) higher insurer profitability, and (iii) increased risk margin in loss reserves. Overall, my findings highlight how changing social norms and legal developments translate into a source of aggregate risk for the insurance sector. Uncertainty induced by the shifting loss distribution is priced by insurers, a finding that is relevant to emerging risks such as climate and cyber.

Keywords: Social norms, Social Inflation, Financial frictions, Jury verdicts, Liability insurance
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1 Introduction

A well-functioning insurance sector, collecting nearly \$1.5 trillion in annual premiums and managing over \$8 trillion of assets, is critical for the financial health of the broader economy. One important feature of the insurance sector is its significant exposure to aggregate risks such as financial market fluctuations and extreme climate events. Understanding these aggregate risks is of first-order importance, as undiversifiable shocks to the insurance sector propagate to asset markets and the real economy – especially in the presence of financial and regulatory frictions (Froot and O'Connell, 1999; Koijen and Yogo, 2015). In this paper, I show that unexpected shifts in the insurers' loss distribution, driven by changing social norms and legal developments, present a novel source of aggregate risk with important economic implications.

The focus of this study is a phenomenon widely referred to as *social inflation* by insurers and regulators, defined as the rise in extreme jury verdicts and settlements above and beyond traditional economic factors. The same event that used to cost a few thousand dollars at court has now become a much costlier liability, often exceeding millions. And as a result, this shifting loss distribution generates significant uncertainty faced by the insurers. The term *inflation* reflects the increased mean and volatility of losses, and the term *social* highlights the influence of social norms on the jury's decision-making process.

Understanding social inflation and its economic implications is important for at least three reasons. First, a stable legal environment is fundamentally important for risk sharing, and consequently disruptions to this environment have wide-ranging implications for firms and institutions.[1] Second, studying how insurers respond to escalated uncertainty due to shifting loss distributions is also informative for understanding their response to emerging risks with similar features such as climate and cyber.[2] And finally, social inflation has emerged as one of the most salient risks in the insurance sector – as Figure 1 shows, social inflation is universally discussed in insurers' earnings calls, begetting regulatory concerns regarding its impact on insurance affordability and passthrough of costs to consumers (NAIC, 2023). Despite these reasons, however, no academic research exists on this topic.

In this paper, I fill this gap by studying the risks and economic consequences of social inflation, focusing on two questions. First, what risk does social inflation pose to the insurance sector? And second, how do insurers respond to social inflation? For the second question, I am particularly interested in disentangling the impact of increases in expected losses (first

[1] Within the insurance sector, the reverberations of social inflation are felt broadly across liability lines that span medical malpractice, directors and officers liability and product liability (NAIC, 2023). Appendix A details the recent developments in each line of business.

[2] In particular, outdated models and changing external factors like climate change have made risk assessment increasingly uncertain for insurers, which mirrors challenges in pricing for social inflation. For example, see: "Are We Ready for a \$100 Billion Catastrophe? How About \$200 Billion?", Wall Street Journal, August 26, 2023, https://www.wsj.com/finance/insurance-catastrophe-reinsurance-hurricane-77a69eab.

moment) from the impact of rising uncertainty (second moment) in the loss distribution.

To answer these questions, I proceed in three steps. First, I use a hedonic regression to show that losses for events with *same* characteristics have increased dramatically over time. This persistent shift is attributed to evolving social norms and legal tactics and leads to substantial uncertainty faced by the insurers. Second, I construct a model to study how insurance pricing responds to increased uncertainty in the loss distribution. It shows that the presence of regulatory and financial frictions induces insurers to charge a risk compensation in their pricing decisions. As a result, insurance prices can increase not only because losses are higher on average but also because they become more uncertain. Finally, I estimate the insurers' price response to social inflation leveraging within insurer-year variation across product lines and geography. I find that social inflation accounts for nearly 70% of the annual price increase since 2018. Consistent with the role of risk compensation in prices, I find bigger hikes for more constrained insurers, higher insurer profitability, and increased risk margin in loss reserves.

As outlined in Section 2, I start by compiling a novel dataset that includes detailed information on historical verdicts and settlements, combined with the annual financial statements of insurers and their historical price (rate) changes. The data on verdicts and settlements include in-depth information for each case, including the date, court, types of injuries, involved parties, and a summary of the facts. To my knowledge, this is the first paper that uses detailed information on verdicts and settlements to study insurer response to such developments.

My empirical analysis focuses on personal injury accidents with motor vehicles, which involve individuals suffering physical harm as a result of negligent actions of others. Such incidents typically give rise to claims under liability insurance, which aims to offer financial compensation to the victims. This focus is for several reasons. First, they constitute the majority of cases in my dataset, providing sufficient variation to identify the impact of social inflation on the insurance sector. Second, the impact of social inflation is thought to be have been most salient in auto insurance, which is directly affected by these accidents (NAIC, 2023). Finally, this setting provides variation in exposure to social inflation across different product lines and across geographies, which proves useful for my empirical analysis.

In the first part of the paper, I provide three stylized facts on social inflation (Section 3): (i) the rise of extreme jury verdicts, (ii) concurrent changes in the loss distribution, and (iii) price response of insurers to these changes. The first fact documents the rise of extreme jury verdicts – the total value of cases greater than $25 million has increased dramatically from roughly $200 million in 2001 to over $1 billion in 2015 and nearly $3 billion in 2019. This trend far outpaces inflation and is robust to other definitions of extreme verdicts. Furthermore, examining the distribution of the entire sample of verdicts reveals a broad-based shift in the loss distribution, not merely an uptick in extreme cases.

The second fact provides a formal evidence of the changing loss distribution by estimating a hedonic model that relates the size of each verdict to quantifiable accident characteristics (e.g., number of deaths). I find that the hedonic model estimated on 2001–2010 data can accurately forecast the verdict sizes in 2011–2014. However, the model significantly understates post-2015 outcomes, resulting in significant forecast errors. This heightened uncertainty arises from shifting model coefficients, which insurers associate with evolving social norms and the changing litigation landscape.

The third fact documents the concurrent pricing patterns for commercial auto insurance, a line of business that is affected by social inflation. I document a stark contrast in pricing behavior of insurers across two periods. Starting in year 2018, more than 90% of insurers increase their prices, and annual price increases exceeding 10% become prevalent. This trend stands in sharp contrast to the pre-2018 period, where price increases are not common and only in small magnitudes.

In the second part of the paper, I then interpret these facts through a model of insurance pricing that extends recent works emphasizing supply-side frictions in insurance markets (Section 4). By emphasizing the role of uncertainty in the loss distribution, the model extends Koijen and Yogo (2022a) to liability insurers and demonstrates how social inflation affects insurers' pricing decisions. Like other models of financial intermediaries, the insurer maximizes firm value subject to regulatory and financial frictions. These frictions capture the fact that equity issuance is costly, and that a low level of capital can lead to a rating downgrade or a regulatory action with adverse consequences in both retail and capital markets.

The main output of the model is an analytical pricing equation for a new insurance policy. The key insight is that insurers demand a risk compensation for holding this risk on their balance sheet, which stems from the interaction of financial frictions and the uncertainty in their capital. As a result, changes in the loss distribution can affect prices through two channels. First, price can increase when each new policy is perceived to be more costly to insure on average. This effect only exists if the first moment of the loss distribution has increased. Second, price can increase due to a corresponding increase in the risk compensation, which stems from the interaction of loss uncertainty and financial frictions.

In the final part of the paper, I use the model as a guide and study the insurers' price response to social inflation (Section 5). The main challenge in quantifying the effect of social inflation on insurance prices is to separate its effect from other drivers of insurance premiums. In the context of insurance, this could be new regulation, consumer demand shocks, or other risk developments unrelated to the legal system. To overcome these challenges and isolate the effect of social inflation, I employ empirical designs that leverage within insurer-year variation in exposure to extreme legal outcomes. Specifically, I exploit the feature that an insurer typically operates in multiple lines of business (e.g. commercial auto) and in multiple states (e.g. Illinois). As a result, we can compare the same insurers' price responses across product lines and states that are differently exposed to social inflation.

In the baseline empirical design, I estimate difference-in-difference by comparing the price changes in commercial auto liability to those in personal auto liability. This comparison is useful for multiple reasons. First, both lines insure financial risks arising from vehicle-related bodily injury, which makes the parallel trends assumption more plausible. Second, the rise in extreme verdicts is only found in cases with corporate defendants but not for those with individual defendants, thereby making the commercial auto liability more exposed. Third, research from the legal literature suggests that for the same behavior, corporations receive higher levels of critique for violations caused by negligent behavior. Altogether, these facts suggest exploiting the type of auto liability lines – commercial auto versus personal auto – as the first source of variation in assessing the impact of changing social inflation on pricing behavior.

To specify the date of treatment, I examine when insurers insurers collectively recognized social inflation as a meaningful systemic risk. To identify this threshold, I leverage data sources offering insight into industry risk perceptions. First, I find that 2018 is the first year in which a majority of insurers have started recognizing social inflation as a material source of risk in their earnings calls. Second, I examine the loss reserves set aside by insurers in anticipation of future liabilities and find that the average dollar loss reserves remain constant until 2018, after which it almost doubles by the end of 2021. Based on these evidence from earnings calls and loss reserves, I compare the price response of insurers before 2018 to that after 2018.

I find that commercial auto liability lines experienced a 4.4 percentage point higher annual price change compared to personal auto lines. This rate differential is economically meaningful, accounting for nearly 70% of the average annual price change for commercial auto liability line post-2018. The estimate is robust to a wide range of controls and different fixed effects specification. By estimating an event-study version of the difference-in-difference, I do not find any evidence of pre-trends in prices across these two lines, which lends further credence to the parallel trends assumption.

To address the potential role of unobservable time-varying factors that affect commercial and personal auto lines differentially (e.g., reinsurance costs), I also employ a triple-difference design by using geography as an additional source of variation. For each state, I compute its exposure to social inflation as the total verdicts greater than $25 million in the 2001–2014 period, scaled by the size of the market in 2014. I find that the difference in price change between commercial and personal auto lines is about 1.5 to 2 percentage points higher in high exposure states, i.e., states with above-median exposure. This magnitude is also economically significant as it represents two thirds of the difference in average price change for low exposure states.

The model suggests that insurers' large price response to social inflation includes both responses to higher expected losses and increased uncertainty. To examine the role of uncertainty, I provide three pieces of empirical evidence suggesting that increasing risk compensation has been an important driver behind the documented price increases.

First, I examine how the price response to social inflation varies across insurers with different levels of financial constraints. Because risk compensation is increasing in the marginal cost of statutory capital, more financially constrained insurers should have greater price increases if risk compensation is driving prices. Based on this insight, I split the sample of insurers into two groups, where the more (less) constrained insurers have the below (above)-median lagged risk-based capital ratio. Estimating the difference-in-differences specification shows that the price differential between commercial and personal is 1.7–3.2 percentage point higher for the more constrained insurers, which is about 50% of the average price increase for the less constrained insurers.

Second, I examine insurers' profitability. The model predicts that an increase in risk compensation should make insurers more profitable even when losses are rising. Estimating the difference-in-differences specification using realized profitability as the dependent variable, I find that insurers' profitability for commercial auto liability increased relative to personal auto liability, with the difference appearing only after 2018. Furthermore, panel regressions show that the difference between the two lines is driven by increasing profitability for commercial auto liability rather than decreasing profitability for personal auto liability. This finding is consistent with the notion of risk compensation, as insurers are being compensated for holding aggregate risk on their balance sheet.

First, I examine the loss reserving behavior of insurers. In loss reserves, insurers add additional loss provision beyond expected losses to account for uncertainty in their loss estimate. Thus, the patterns in reserving decisions provide a useful window into the risk perceived by insurers. I estimate an empirical model of loss reserves and find that this model estimated on the 2005–2010 data can accurately predict the reserves in 2011–2017, but it underestimates post-2018 reserves by nearly 40%. These patterns suggest that the risk perceived by the insurer has increased dramatically, above and beyond increase in expected losses.

I conclude by conducting additional empirical analyses to test alternative explanations for the observed pricing patterns but find limited support. For instance, stable market concentration in both lines, with personal auto liability even showing higher levels, makes it less likely that increase in markup is the key factor. Furthermore, greater reduction in equilibrium quantities for commercial auto liability relative to personal auto liability suggests that demand shifts are likely not the main driver of increased insurance prices. Theories involving collusive behavior of insurers have shortcomings in fully explaining the observed trends in loss reserves and the stark differences in pricing across commercial and personal auto markets, which feature a similar set of key players. Taken together, these points lend support to this study's central finding that social inflation and the accompanying uncertainty has played a meaningful role in shaping insurers' pricing and reserving decisions.

Related Literature

This paper relates to three strands of the literature: (i) legal and social factors in financial markets, (ii) risks and frictions in insurance markets, and (iii) capital effects in intermediary asset pricing.

First, this paper contributes to the literature that studies the role of legal and social factors for financial markets. Since the pioneering work by La Porta et al. (1998), the literature at the intersection of law and finance has addressed the role of legal institutional environments in a range of issues including long-term growth (La Porta et al., 1997; Selvin and Picus, 1987; La Porta et al., 2006; Glaeser et al., 2004), competitiveness of the economy (Zingales, 2006; Kempf and Spalt, 2019), investments (Kaplan et al., 2003; Lerner and Schoar, 2005), investor protection (Atanassov and Kim, 2009; Fernandes et al., 2010; Acheson et al., 2019) and shareholder activism (Klein and Zur, 2009). In the context of insurance, Gennaioli et al. (2020) illustrates how the level of trust and the quality of the legal system can shape equilibrium insurance contracts. My paper complements these papers by focusing on the supply decisions of insurers and illustrating how a particular dimension of the legal system – the jury system interacted with changing social norms – can shape insurance markets in meaningful ways.

My paper also focuses on jury verdicts and settlements, a relatively unexplored dimension of the U.S. legal system within the finance literature. Existing literature has focused on two main aspects of the jury system: (i) implications of the jury system for economic outcomes (e.g., Rose et al., 2018; Anwar et al., 2022), and (ii) firm responses to the jury system (e.g., Cohen and Gurun, 2023). My paper intersects with both these domains but introduces new angles. My textual analysis suggests that shifts in social norms can permeate the jury system, thereby influencing verdicts and settlements. Furthermore, my results imply that insurance companies, who are directly affected by verdict outcomes, have strong incentives to influence the legal system.

My paper also relates to a growing literature that studies the implications of social norms for financial markets. A growing literature has focused on how social norms affect a particular group of economic participants, which then affects financial markets through their activities. For example, the literature on ESG investing studies how changing non-pecuniary preferences of investors determine risk premia and firm valuations (e.g. Hong and Kacperczyk, 2009). On the firm side, recent research have looked at how social norms affect corporate financing (e.g. Houston and Shan, 2022). There is also research looking at how changing social norms affect policymaking and regulatory decisions. Recently, Colonnelli et al. (2022) provide empirical evidence linking public perceptions of corporate behavior to the support for economic policies. My paper examines a more direct channel of how social norms impact the financial sector, as the rise of extreme verdicts and settlements represent one particular manifestation of changes in social norms.

Second, this paper unveils a novel source of aggregate risk in the insurance sector. The existing literature commonly identifies three primary sources of aggregate risk. First is the financial market where studies have examined the role of stock market volatility (Foley-Fisher et al., 2021; Koijen and Yogo, 2022a), interest rate mismatch (Hartley et al., 2017; Ozdagli and Wang, 2019; Koijen and Yogo, 2022b) and market liquidity (Foley-Fisher et al., 2020). The second source is catastrophes such as natural disasters (Gron, 1994; Froot and O'Connell, 1999; Oh et al., 2021; Jung et al., 2023) and emerging threats like pandemics and cyber incidents. Finally, the third source is policyholder risk, which may arise from demographic changes (Cutler, 1996) or behavioral shifts (Gottlieb and Smetters, 2021; Koijen et al., 2022). Distinct from these three strands of the literature, my paper examines the aggregate risk induced by changes in the legal landscape, which directly shapes the liabilities that insurers face.[3] I show that unexpected shifts in the loss distribution, induced by the changing social norms and legal environment, can have a profound aggregate impact on the pricing behavior and operations in the insurance market.[4]

My paper also relates to a broader literature that stresses the role of financial and regulatory frictions for insurance company behavior, which has been shown to affect product pricing (Gron, 1994; Froot and O'Connell, 1999; Zanjani, 2002; Koijen and Yogo, 2015; Sen and Humphry, 2018; Koijen and Yogo, 2022a; Ge, 2022; Liu and Liu, 2023), portfolio choice (Ellul et al., 2011; Ellul et al., 2015; Ge and Weisbach, 2021; Ellul et al., 2022; Becker et al., 2022; Koijen and Yogo, 2023), and risk management decisions (Koijen and Yogo, 2016; Sen, 2023). My paper extends this literature by emphasizing the risk compensation that arises from the interaction of these frictions with the uncertainty in the loss distribution and highlighting its role for product pricing.

Third, this paper contributes to the literature that studies the asset pricing implications of shocks to the capital of financial intermediaries.[5] As He and Krishnamurthy (2018) notes, typical shocks to intermediation include decreases in capital caused by losses or increased complexity of investments that worsen the moral hazard friction. My paper studies a distinct shock from the legal environment that increases uncertainty in capital orthogonal to other economic risks. As insurers are the marginal investors in the market for insurance, this risk is

[3] More broadly, there is a significant literature on the economic consequences of uncertainty (e.g., Bloom, 2014). Among many forms of uncertainty that has been explored in this literature, one that is closest to my context is the notion of legal uncertainty (Lefstin, 2006; Farnsworth et al., 2010; Lee et al., 2022).

[4] My findings also pertain to the understudied U.S. liability crisis of the mid-1980s, characterized by significant fluctuations in insurance pricing and availability. Previous studies have emphasized the role of uncertainty and capacity constraints in this crisis (Tort Policy Working Group, 1987; Winter, 1988; Winter, 1991). I contribute to this discussion by bringing in novel and granular data and establishing causality using modern econometric techniques, thereby confirming narratives from earlier literature.

[5] There is a large empirical literature that focuses on specific financial intermediaries and traces out their impact on various asset markets (Mitchell et al., 2007; Etula, 2009; Mitchell and Pulvino, 2012; Hu et al., 2013; Adrian et al., 2014; He et al., 2017; Du et al., 2018; Siriwardane, 2019; Haddad and Sraer, 2020; Haddad and Muir, 2021). Relatedly, a large banking literature provides evidence that shocks to capital affect bank lending (e.g. Peek and Rosengren, 1997; Kashyap and Stein, 2000; Ashcraft, 2005; Paravisini, 2008; Aiyar et al., 2014). On the theoretical side, works such as He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) show how asset prices are tied to intermediary capital in the presence of financial frictions.

nonetheless priced in this market. In this respect, it resonates with a body of work showing that market-specific risk factors have important effects on risk premia, including mortgage backed securities (Gabaix et al., 2007), corporate bonds (Collin-Dufresne et al., 2001), and credit default swaps (Berndt et al., 2005).

Roadmap Section 2 briefly discusses the data and the institutional setting, and Section 3 provides three stylized facts on social inflation. Section 4 provides a model of insurance pricing with social inflation, and Section 5 provides empirical evidence on insurers' response to social inflation and the role of risk compensation. Section 6 discusses implications for the real sector. Section 7 concludes.

2 Data and Institutional Background

This study focuses on personal injury accidents arising from motor vehicles, which are incidents where individuals sustain physical harm due to others' negligent actions involving motor vehicles. These events typically trigger claims under liability insurance, which is designed to provide financial compensation for the victim. For instance, if a commercial truck driver injures a pedestrian, the company's commercial auto liability insurance covers the compensation to the victim, up to the specified policy limit.

Focusing on these incidents as my empirical setting offers three key advantages. First, they constitute the majority of cases in my dataset, providing sufficient variation to identify the impact of social inflation on the insurance sector. Second, social inflation is thought to be most prevalent in auto liability insurance, which is directly affected by these accidents (NAIC, 2023). Finally, this setting provides variation in exposure to social inflation across different product lines and across geographies, which proves useful for my empirical analysis described in Section 5.

Data I first describe the data, and Appendix B provides greater details and summary statistics. For my empirical analyses, I construct a dataset that combines (i) historical jury verdicts, (ii) insurance prices (rates), (iii) insurers' textual data, and (iv) insurers' financial data. First, I obtain historical data on jury verdicts from VerdictSearch, a comprehensive database that compiles case summaries based on feedback from both plaintiffs and defendants.[6] Second, I obtain information on insurance rates from two sources: (i) annual market survey conducted by the Council of Insurance Agents & Brokers (CIAB) and (ii) rate filings of insurers through S&P Global. Third, I obtain transcripts of earnings conference calls of major insurers from Capital IQ. Finally, I obtain historical balance sheet information of insurers from S&P Global.

[6]The database also provides information on settlements. When a personal injury claim is settled out of court, however, the settlement amount and details of the case are not public record. Incorporating settlements into the analysis yields qualitatively similar trends over time.

I implement two filters in constructing my final sample of property and casualty insurers. First, I exclude insurers with negative assets. Second, I exclude insurers with net premiums written less than \$100,000 to focus on firms with meaningful operations. The final sample consists of 1,794 insurers from 2001 to 2021.

Institutional Background I briefly describe the institutional background for this study, and Appendix C provides greater details. This study examines developments at the intersection of insurance markets and the underlying legal system. The U.S. jury system effectively serves as a conduit for social norms, shaping verdicts that reflect evolving attitudes towards liability. Insurers are directly exposed to these outcomes, as they are obliged to cover the payments necessitated by these legal decisions.

While jury verdicts are not binding legal precedents, extreme jury verdicts can affect the size of future verdicts and settlements. First, accumulated insights from past verdicts enhances litigation tactics, thereby contributing to future larger verdicts and settlements. These tactics often include strategic choices of jurisdiction and the deployment of specialized litigation strategies.[7] Second, the awareness of outcomes from prior cases can also serve as an informational baseline for both the plaintiffs and defendants, influencing the willingness to take a case to court. Finally, the promulgation of large cases can recalibrate jury expectations, thereby affecting their award amounts in subsequent cases.[8]

Like banks and other financial intermediaries, insurers operate within a complex regulatory environment. They use sophisticated risk modeling techniques to estimate loss distributions and set insurance rates, primarily relying on historical data. To ensure financial stability, insurers must meet minimum capital and surplus requirements as well as risk-based capital (RBC) requirements. Furthermore, they are also obligated to maintain sufficient reserves for future claims according to the statutory accounting principles provided by the National Association of Insurance Commissioners (NAIC), which serves as the de facto regulatory body for the U.S. insurance industry.[9] In particular, insurers are required to take into account the degree of uncertainty inherent in their loss projections, making reserves a useful window into their risk perceptions (Committee on Property and Liability Financial Reporting, 2020).

A key decision for insurers is setting the prices charged for policies. When insurers update loss projections or other factors that enter their pricing models, they file for "rate changes" –

[7] One example is a litigation tactic referred to as the "reptile theory." The "reptile theory" refers to a litigation strategy popularized in 2009 that aims to appeal to jurors' primitive instincts, essentially urging them to protect their community from a perceived threat by awarding larger damages. The name derives from its focus on engaging the reptilian complex of jurors' brains, which controls basic survival instincts.

[8] One prominent example is the Tracy Morgan settlement, which involved a 2014 collision with a Walmart truck that resulted in serious injuries to a renowned comedian Tracy Morgan and the death of a passenger. The case attracted widespread media attention and set a precedent for large settlements in personal injury cases, thereby influencing juror expectations.

[9] Typically, reserving is considered to be more challenging for property and casualty insurers than for life insurers. As a result, loss reserves feature prominently in the risk-based capital calculations for property and casualty insurers but not for life insurers (American Academy of Actuaries Joint RBC Task Force, 2002).

the average percentage change in prices resulting from the proposed update to their pricing models. These filings, which are made separately for each product line, contain their revised risk assessments and are submitted for approval by state insurance regulators, who examine the request and may adjust the proposed rates before granting approval (Oh et al., 2021). Regulatory oversight tends to be more intensive for personal insurance lines than commercial lines as consumer protection is a greater concern for personal policies.

3 Three Stylized Facts on Social Inflation

In this section, I provide three stylized facts on social inflation. First, I document the rise of extreme verdicts over the past decade, a phenomenon often termed "social inflation" within the insurance sector (Fact 1). Using a hedonic regression, I then show that this rise is driven by changes in how characteristics of each accident are valued by the jury at court. (Fact 2). And as losses have become larger and more uncertain over time, insurers have responded by raising prices (Fact 3). In subsequent sections, I interpret these facts through a model (Section 4) and formal empirical tests (Section 5).

3.1 Fact 1. Trends in Jury Verdicts

Figure 2 summarizes the recent trends in jury verdicts. Panel (a) first shows the total sum of verdicts exceeding \$25 million in each year throughout the sample. The total compensation has increased dramatically, surging from roughly \$200 million in 2001 to over \$1 billion in 2015 and over \$2 billion in 2019. In 2020, we do not see a similar increase as the courts were closed to the COVID-19 pandemic, yet the trend continues to 2021 where we see nearly \$3 billion in total outcomes. Figure A1 shows that a similar trend exists for different definitions of extreme cases, and Figure A2 shows that the rise is not driven by an increased duration from the time of the accident to the verdict. In addition, panel (a) of Table A1 shows that this upward shift is not confined to the extreme tails but is also present for other moments of the distribution. This pattern indicates a persistent change in the entire loss distribution, rather than merely a transitory uptick in the occurrence of extreme outcomes.

Insurers have increasingly identified these shifts as a significant risk factor in their operations. As mentioned in the introduction, Figure 1 displays the proportion of top 15 insurance groups that discuss social inflation in their earnings calls. It illustrates a notable uptick in these discussions beginning in 2018, reaching a point by 2020 where almost all insurers cover the topic.[10] Importantly, insurers' earnings calls not only emphasize the rising expected losses, but also highlight the increased uncertainty surrounding these trends (Figure A4). This

[10] Figure A3 confirms this trend by showing the uptick in the total mentions of "social inflation" as well as the share of total earnings calls discussing "social inflation" over time.

heightened perception of risk is also shared with regulators who echo concerns about both the escalating losses and accompanying uncertainty (Figure A5).

3.2 Fact 2. Drivers of the Shift in the Loss Distribution

A Hedonic Model of Verdicts This rise in extreme verdicts is consistent with two explanations. On one hand, the severity (or other characteristics more broadly) of these accidents may have changed, leading to higher associated verdicts. For example, if accidents now result in more severe injuries or fatalities, payouts would naturally rise to compensate for these elevated damages. Alternatively, the mapping from accident characteristics to compensation could be shifting. This would mean that an accident with identical features could lead to higher verdicts now compared to previous years.

I distinguish these two explanations through the lens of a hedonic regression (Rosen, 1974). The underlying idea behind this approach is that if two cases with identical accident profiles result in significantly different verdicts over time, this discrepancy could be indicative of a change in the valuation of these characteristics at court. The application of the hedonic regression model allows for such a comparison to be conducted at a large scale, enabling a more systematic analysis of these trends over time.[11]

To this end, I first estimate the following regression for cases greater than $1 million from 2001 to 2010:

$$y_i = \gamma_0 + \sum_c \gamma_c x_{c,i} + \epsilon_i \tag{1}$$

where y_i is the log amount of case i in $ millions and $x_{c,i}$ refers to the cth characteristic for case i. γ_c thus represents the marginal contribution or the "hedonic price" of characteristic c. The set of characteristics include number of deaths, number of plaintiffs, dummies for the 10 most common injury types, number of attorneys, number of experts, and dummies for each state. I also include the CPI and the medical CPI (normalized to 2001 value) for each year. Using the coefficients estimated from the 2001–2010 period, I then forecast the size of each verdict in the post-2010 sample. Importantly, I use the actual characteristics of each case, so the discrepancy between actual and the predicted value is attributed to the differences in coefficients.[12]

[11] As a motivating example that illustrates the intuition behind the hedonic regression, consider the following two cases summarized in Table A2. In the first case from 2012, a female plaintiff was injured in a car accident involving a Coca-Cola employee and awarded $1,106,206 for her injuries, which included herniated cervical and lumbar discs, and bilateral carpal tunnel syndrome necessitating multiple surgeries. A decade later, in 2022, another female plaintiff, suffering from similar severity of injuries but without needing surgeries, was awarded $5,000,000 in damages against Amazon and its driver. The dissimilar compensation for similar accident profiles may indicate a change in how such characteristics translate into compensation amounts.

[12] This exercise is essentially equivalent to the Oaxaca-Blinder decomposition, a method often used to decompose differences in mean outcomes into a portion attributable to differing characteristics and another portion due to varying valuation or treatment of those characteristics (Blinder, 1973; Oaxaca, 1973). In this context, the former would reflect changes in the accident characteristics, and the latter would capture shifts in how these characteristics are valued in determining the jury verdicts.

Figure 3 presents the results of the forecasting exercise. In panel (a), the red dotted line indicates the average predicted amount with the 95th confidence interval, while the solid gray line represents the actual sample average.[13] It shows that the model trained on 2001-2010 data reasonably predicts the cases up to 2014. However, post-2015, a divergence starts to emerge. Since the predicted amount remains essentially flat, the post-2015 surge mainly arises from evolving mappings from accident characteristics to verdicts. Panel (b) also shows the mean squared error from the forecasting exercise and shows that compared to 2011, it is about 40% larger. By focusing on the characteristics of individual cases and how they are valued by the jury, these results thus suggest that the rise in extreme verdicts is not driven mechanically by an increase in the number of accidents or increase in average accident severity.[14]

Which coefficients? To examine which coefficients have changed over time, I estimate an additional model using the 2011–2021 data. Figure 4 presents the coefficients on select variables for the 2001–2010 and 2011–2021 periods, from which two key findings emerge. First, most coefficients yield positive point estimates, supporting the notion that these characteristics generally lead to higher payouts. Second, compared to the 2001-2010 period, the coefficient on the number of deaths have increased notably. Specifically, an additional death is now associated with a 15 to 20% larger compensation on average.

To complete the discussion of what drives these changing coefficients, I conduct a textual analysis of white papers and reports on social inflation written by major insurers and other related organizations (see Appendix F for further details). Figure A7 shows that insurers point to three major drivers of social inflation: (i) evolving social norms regarding liability, (ii) a rise in litigation funding and advertising, and (iii) advanced litigation tactics. I also find that insurers find these variables difficult to quantify and incorporate into risk models, exacerbating the uncertainty in their loss distribution. Overall, these findings underscore the shifts in how accident features are priced by the jury, amplifying the uncertainty in insurers' loss distribution.

Impact on Insurer Losses I next provide evidence that this shift had also led to a persistent impact on insurers' losses, i.e. the total amount of claims paid by the insurers. Panel (a) of Figure 5 plots the aggregate realized losses for commercial auto liability in the U.S. insurance sector, adjusted for inflation. In the 2000s, the yearly losses have been consistently around $8 billion per year, which exhibits a small downward trend when adjusted for inflation. Starting 2014, the losses start rising each year, reaching nearly $10 billion in 2019 and onwards. To summarize, aggregate losses have risen by 32% from 2014 to 2021.

Concurrently, the variability of losses have also increased. As within-insurer dispersion in losses is not observed in the data, I compute the cross-insurer dispersion in losses as measured

[13] Standard errors are obtained through bootstrapping with 1000 samples drawn with replacement, maintaining the same number of cases for each year in the sample.

[14] If anything, Figure A6 suggests that the number of accidents has actually decreased over this time period.

by the inter-quartile range. Panel (b) of Figure 5 shows that the variability of losses have stayed relatively constant in the 2000s, but it starts to rise steeply starting in 2011. Specifically, the dispersion has increased by 110% from 2011 to 2021.

3.3 Fact 3. Trends in Insurance Prices

Finally, I show how prices in an affected line of business have changed concurrently with the shifts in the loss distribution. For this exercise, I use the data from the Council of Insurance Agents & Brokers (CIAB) survey, which solicits information from commercial insurance brokers regarding their rate change behavior for select commercial insurance lines.[15]

Figure 6 summarizes the concurrent trends in insurance prices. Panel (a) plots the proportion of brokers reporting an increase / no change / decrease in prices for commercial auto liability. It reveals a stark contrast in pricing behavior across two periods: prior to 2018, around half of the surveyed brokers report an increase on average, while post-2018 almost every broker reports a hike in their prices. This pattern resonates with the pervasive, non-diversifiable nature of social inflation, as it appears to influence the behavior of insurers universally.

In panel (b), I zoom in on brokers reporting an increase in rates and present the distribution of the magnitudes of the price changes. It shows that before 2018, the annual price increases were predominantly in the 1–9% range, while increases of 10–19% and above 20% have been quite rare. Post 2018, however, large rate changes exceeding 10% become quite common, reaching more than 50% of the brokers by the end of 2019 and end of 2020. Overall, these patterns strongly indicate a marked shift in the insurers' pricing behavior, aligning with the shifts in the loss distribution faced by the insurers.

4 A Model of Insurance Pricing with Social Inflation

The previous section documents a persistent shift in the loss distribution faced by insurers, leading to both higher losses and uncertainty. In this section, I develop a model of optimal insurance pricing that illustrates how social inflation affects the pricing of insurance. The model builds on recent models emphasizing supply-side frictions in insurance markets (Gron, 1994; Froot and O'Connell, 1999; Koijen and Yogo, 2022a). Section 4.1 first provides a descriptive overview of the model. I then proceed to details of the model in Section 4.2 and provide the optimal pricing equation in Section 4.3.

[15] The main advantage of the CIAB survey is that it provides aggregate pricing trends and avoids the idiosyncracies of state-level regulations that are not present in the rate filings data. Later for the main empirical analyses presented in Section 5, I use the price change information from the rate filings of insurers. Appendix B provides further information on the CIAB survey.

4.1 Overview

An insurer sells L types of policies, indexed by $\ell = 1, ..., L$, and faces a downward sloping demand curve $Q_\ell(P)$ for each type ℓ, where $Q'_\ell(P) < 0$.[16] The different types of policies are differentiated not only by lines of business (e.g., commercial auto liability) but also by geography (e.g., Illinois). Each policy type ℓ covers random loss $\tilde{V}_\ell$, characterized by mean μ_ℓ and variance σ^2_ℓ. I use $\tilde{}$ to denote variables that are random at the time of insurance pricing and denote the cumulative distribution function of $\tilde{V}_\ell$ as F_ℓ. The insurer aims to maximize firm value in the presence of financial frictions, which is modeled as a convex cost function of statutory capital.

The key insight from the model is that insurers demand a risk compensation for holding the risk of social inflation on their balance sheet. As a result, changes in the loss distribution can affect prices through two channels. First, price can increase when each new policy is perceived to be more costly to insure on average. This effect only exists if the first moment of the loss distribution has changed. Second, price can increase due to a corresponding increase in the risk compensation, which stems from the interaction of loss uncertainty and financial frictions.

4.2 Model

Balance Sheet Dynamics At the start of the period, the insurer has assets A_0 and liabilities L_0. The insurance company's assets after the sale of new policies, is

$$A = R_A A_0 + \underbrace{\sum_{\ell=1}^{L} P_\ell Q_\ell}_{\text{Proceeds from sales}} \tag{2}$$

where R_A is an exogenous return on its existing assets.

As discussed earlier in Section 2, insurers are required to set aside adequate reserves to cover future losses according to the statutory accounting principles provided by the NAIC. In determining the level of reserves, insurers follow the Statement of Statutory Accounting Principles (SSAP) No. 55, which requires that reserves take into account the uncertainty inherent in the estimation process. Furthermore, insurers are required to annually provide statement of actuarial opinion (SAO) regarding their reserves, which is filed by an actuary that attests to the adequacy of the reserve amounts.[17]

[16]The downward sloping demand curve is reasonable given the role of brand differentiation in the insurance market. Even though insurance is often considered a standardized product, consumers differentiate between providers based on factors like brand reputation and customer service. The downward-sloping demand curve can also be motivated by an industry equilibrium subject to search frictions, such as Hortaçsu and Syverson (2004). As the precise micro-foundations are not essential for this paper, I take the demand curve as exogenously given.

[17]The Actuarial Standard of Practice No.43 suggests that actuaries "consider the implications of uncertainty

To mimic the insurer's actual reserving decision, I assume the insurer sets the dollar reserve of each policy such that it covers the losses up to the $(1-\alpha)$th worst cases, i.e. equal to $F_\ell^{-1}(\alpha)$. This assumption is consistent with the reserving practice of insurers who typically choose a high percentile of the loss distribution by adding a risk margin to expected losses (SwissRe, 2014; Progressive, 2021).[18] Therefore, the insurer's liabilities evolve according to:

$$L = R_L L_0 + \underbrace{\sum_{\ell=1}^{L} F_\ell^{-1}(\alpha)\, Q_\ell}_{\text{New Liabilities}} \tag{3}$$

where R_L is an exogenous return on its liabilities (e.g., inflation, cost of adjustments).

I define the insurance company's statutory capital as its equity relative to the required capital:

$$K = \underbrace{A - L}_{\text{Equity}} - \underbrace{\kappa L}_{\text{Required Capital}} \tag{4}$$

where κ is the risk charge on liabilities, exogenously determined by regulation. Together, the equations imply that the statutory capital evolves according to:

$$K = R_K K_0 + \sum_{\ell=1}^{L} \left(P_\ell - (1+\kappa)\, F_\ell^{-1}(\alpha) \right) Q_\ell \tag{5}$$

where

$$R_K = \frac{A_0}{K_0} R_A - \frac{L_0}{K_0}(1+\kappa)\,. \tag{6}$$

Financial Frictions Like other financial institutions, insurers face financial frictions in several forms. First is capital market frictions such as moral hazard or asymmetric information. Second, a low level of statutory capital K can lead to a rating downgrade, which can have adverse consequences in retail markets (Epermanis and Harrington, 2006). Third, regulators monitor insurers by scrutinizing insurers' level of capital, which typically happen before insurers fall below the minimum risk-based capital requirement (Ge, 2022).

To capture these financial frictions in a parsimonious fashion, I follow Koijen and Yogo

in loss and loss adjustment expense reserve estimates in determining a range of reasonable reserve estimates." (Actuarial Standards Board, 2011).

[18] Note that the insurer's reserving decision can be also micro-founded as minimizing ϕ_ℓ subject to $\mathbb{P}\left(\phi_\ell \geq \tilde{V}_\ell\right) = \alpha$, i.e. the insurer chooses reserves ϕ_ℓ such that it is sufficient to cover the losses with a very high probability α. The solution to this problem is $\phi = F_\ell^{-1}(\alpha)$. Another way to model the reserve decision is to express it as the expected loss μ_ℓ multiplied by a risk margin $\delta\sigma$, i.e., $\phi_\ell = \mu_\ell \times \delta\sigma$, where the risk margin is a linear function of the volatility σ. Adopting this expression for the reserves ϕ_ℓ yields similar results from the model.

(2022a) and model the cost of financial frictions through a continuous cost function:

$$C = C(K) \tag{7}$$

where $C(\cdot)$ is continuous, twice continuously differentiable, strictly decreasing and strictly convex.[19] C is strictly decreasing because insurers benefit from having a large statutory capital, and C is strictly convex because the benefits of having higher statutory capital decreases in the level of capital. For example, Ellul et al. (2015) and Koijen and Yogo (2015) provide evidence that asset allocation and liability pricing decisions are especially sensitive to risk-based capital at low levels, consistent with a convex cost function.

To simplify notation, I define the marginal cost of capital as c :

$$c = -\frac{\partial C}{\partial K} > 0.$$

Given the convexity of C, it follows that the marginal cost of capital is decreasing in K.

Profits and Firm Value The insurer's economic profit is defined as:

$$\tilde{\Pi} = \sum_{\ell=1}^{L} \left(P_\ell - \tilde{V}_\ell\right) Q_\ell \tag{8}$$

The insurer then chooses the price P to maximize firm value:

$$J = \mathbb{E}\left[\tilde{M}\tilde{\Pi}\right] - C(K) \tag{9}$$

where $\tilde{M}$ is an exogenous stochastic discount factor. Regarding this maximization problem, two further comments are necessary. First, while extreme verdicts and settlements pose a significant risk to the entire insurance sector, they are still idiosyncratic relative to the entire economy. For this reason, I assume that the insurer discounts profits deterministically at the risk-free rate, setting $\tilde{M} = 1$.

Before deriving the optimal price of insurance, I make the following assumptions:

Assumption 1. *For all lines of business ℓ, the αth quantile of the distribution of $\tilde{V}_\ell$ is increasing in σ_ℓ for the α used by the insurer:*

$$\frac{\partial F_\ell^{-1}(\alpha)}{\partial \sigma_\ell} > 0. \tag{10}$$

This assumption states that the value-at-risk, represented by the αth quantile of the dis-

[19] One micro-foundation of the cost of financial frictions is a risk-based capital constraint is of the following form: $\mathbb{P}\left(\tilde{K} \geq K^*\right) \geq \alpha$ where α is a probability threshold very close to 1. In other words, the statutory capital must be kept above a certain threshold K^* with a very high probability. The convex nature of this value-at-risk constraint is echoed in the cost function's own convexity, yielding analogous optimal pricing equations.

tribution of $\tilde{V}_\ell$ where α is close to 1, is increasing in the uncertainty in the loss distribution. In Section 5.3.3, I provide evidence of increased σ_ℓ by examining loss reserves set aside by insurers, which serve as a useful proxy for $F_\ell^{-1}(\alpha)$.

Assumption 2. *For all lines of business ℓ, Q_ℓ is weakly increasing in σ_ℓ :*

$$\frac{\partial Q_\ell}{\partial \sigma_\ell} \geq 0.$$

This assumption states that the demand for insurance may increase in response to an increase in uncertainty, which is consistent with empirical evidence documenting that consumers are willing to pay more for insurance when risks are uncertain (e.g., Gandhi et al., 2021).

4.3 Optimal Insurance Pricing

I now solve for the optimal price of insurance policy. Using the first-order condition with respect to P_ℓ, I obtain the optimal price:

Proposition 1. *The optimal price of insurance for policy type ℓ is given as:*

$$P_\ell = \left(1 - \frac{1}{\epsilon_\ell}\right)^{-1} (\mu_\ell + \beta_\ell \lambda) \tag{11}$$

where ϵ_ℓ is the elasticity of demand for type ℓ and

$$\beta_\ell = (1+\kappa) F_\ell^{-1}(\alpha) - \mu_\ell, \quad \lambda = \frac{c}{1+c}.$$

The proposition shows that the price equals markup times marginal cost, which includes both expected losses (μ_ℓ) and risk compensation ($\beta_\ell \lambda$). First, the markup term is inversely related to the demand elasticity, which emerges in a standard monopolistic competition setting. Furthermore, μ_ℓ in the pricing equation captures the intuition that insurance should be more expensive for policies that have higher expected losses.

The term $\beta_\ell \lambda$ represents the risk compensation, which is a product of the "quantity" of risk β_ℓ and the "price" of risk λ. β_ℓ captures the notion that insurers require a larger risk compensation if there is more risk, represented by $F_\ell^{-1}(\alpha)$. Furthermore, λ captures the idea that capital is costly, since insurers must hold additional capital to safeguard against the risks they underwrite.

Proposition 2. *Both the quantity of risk β_ℓ and the price of risk λ are increasing in σ_ℓ, i.e.,*

$$\frac{\partial \beta_\ell}{\partial \sigma_\ell} > 0, \quad \frac{\partial \lambda}{\partial \sigma_\ell} > 0.$$

As a result, the risk compensation $\beta_\ell \lambda$ is also increasing in σ_ℓ.

This proposition clarifies the implications of rising uncertainty ($\sigma_\ell \Uparrow$) on the risk compensation ($\beta_\ell \lambda$). Specifically, as σ_ℓ increases, both the quantity of risk and the price of risk are affected. Importantly, the increase in β_ℓ is specific to each line of insurance, while the increase in λ affects the entire insurer since elevated uncertainty raises the cost of statutory capital across the insurer's entire portfolio.

Jointly, Propositions 1 and 2 elucidate how social inflation affects prices by impacting both μ_ℓ and $\beta_\ell \lambda$. In Section 5.2, I estimate the insurer price response to social inflation, which captures the combined effects on both μ_ℓ and $\beta_\ell \lambda$.

Proposition 3. *The price of risk λ is decreasing in K_0, i.e.*

$$\frac{\partial \lambda}{\partial K_0} < 0.$$

This proposition identifies one contributing factor that increases the price of risk through increased marginal cost of statutory capital c. In Section 5.3.1, I provide related empirical evidence by comparing the price response of insurers based on their lagged risk-based capital ratios.

The optimal pricing equation also provides an expression for the insurer's expected profitability, where profitability is defined as one minus the ratio of realized losses to premiums:

$$\mathbb{E}\left[\tilde{R}_\ell\right] \equiv \mathbb{E}\left[1 - \frac{P_\ell - \tilde{V}_\ell}{P_\ell}\right] = 1 - \frac{1}{\left(1 - \frac{1}{\epsilon_\ell}\right)^{-1}} \frac{\mu_\ell}{\beta_\ell \lambda} \tag{12}$$

Proposition 4. *Insurer's expected profitability $\mathbb{E}\left[\tilde{R}_\ell\right]$ is increasing in uncertainty σ_ℓ, i.e.,*

$$\frac{\partial \mathbb{E}\left[\tilde{R}_\ell\right]}{\partial \sigma_\ell} > 0.$$

The proposition reinforces the notion of a risk compensation – the intuition that insurers are compensated for bearing risk. It suggests that increases in risk compensation can, in fact, lead to higher expected profitability, even in the face of rising average losses. In Section 5.3.2, I provide empirical evidence of increasing profitability, which is consistent with insurers charging a higher risk compensation. This proposition also provides a theoretical explanation for recent reports that question the impact of social inflation on insurance pricing by pointing to increasing insurer profitability (Hunter et al., 2020).

5 Insurers' Response to Social Inflation

The preceding sections have established a marked shift in insurers' loss distribution. This shift not only inflates the cost per policy but also elevates the risk compensation demanded by insurers. In this section, I first quantify the total effect of these changes on insurance pricing (Section 5.2) and highlight the role of risk compensation in the pricing response (Section 5.3). I then address alternative interpretations of the price response (Section 5.4) and provide results on insurer exits (Section 5.5).

5.1 Sample

To study insurer's price response, I use the historical rate filings of insurers. These filings are publicly available documents that outline proposed premium changes by line of business and by state, enabling a standardized comparison across diverse policies. The key variable of interest is the *rate impact*, which quantifies the average change in premiums from one period to the next for a particular line of business.[20] Utilizing this variable enables a standardized analysis across insurers and across product lines as it abstracts from individual policy specifics. In constructing the sample of insurer rate filings, I concentrate on lines of business that provide auto liability coverage as summarized in Table A3.

5.2 Insurer Price Response to Social Inflation

The main challenge in quantifying the effect of social inflation on insurance prices is to separate its effect from other drivers of insurance premiums. For insurance, this could be new regulation, consumer demand shocks, or other risk developments unrelated to the legal system.

To isolate the effect of social inflation, I employ empirical designs that leverage within insurer-year variation in exposure to extreme legal outcomes. Specifically, I exploit the feature that an insurer typically operates in multiple states and in multiple lines of business. As a result, we can compare the same insurers' price responses across product lines and states that are differently exposed to social inflation. The first empirical design is a difference-in-difference, which uses variation across product lines and over time (Section 5.2.1). Second, to address the remaining concern about time-varying confounders that vary across product lines, I estimate a triple-difference specification by adding geographic variation (Section 5.2.2).

[20] See Oh et al. (2021) for a detailed discussion of rate-setting behaviors of insurers.

5.2.1 Evidence from Difference-in-Difference Design

Cross-sectional Variation In the difference-in-difference, I compare the price changes in commercial auto liability to those in personal auto liability. This comparison is useful for multiple reasons. First, both lines insure financial risks arising from vehicle-related bodily injury, which makes the parallel trends assumption more plausible. Second, despite similarity in the risks they insure, commercial auto liability lines are much more exposed to social inflation than personal auto lines. For example, panel (a) of Figure 7 shows that the number of cases greater than $25M increases steeply for those with corporate defendants, but not for those with individual defendants. As a result, as panel (b) of Figure 7 illustrates, the hedonic model trained on 2001–2010 data results in significant forecast errors only for cases with corporate defendants. Third, research from the legal literature suggests that for the same behavior, corporations receive higher levels of critique for violations caused by negligent behavior. (Haran et al., 2016). Altogether, these insights suggest exploiting the type of auto liability lines – commercial auto versus personal auto – as the first source of variation in assessing the impact of changing social inflation on pricing behavior.

Date of Treatment To operationalize the difference-in-difference, the date of treatment needs to be determined. Given the central focus on insurer pricing responses, the relevant date is when insurers collectively recognized social inflation as a meaningful systemic risk. To identify this timing, I leverage two key data sources offering insight into the industry's risk perceptions. First, I examine the discussion of social inflation in insurers' earnings calls. I find that 2018 is the first year in which a majority of insurers have started recognizing social inflation as a material source of risk in their earnings calls (Figures 1, A3). Second, I examine the loss reserves set aside by insurers in anticipation of future liabilities. Figure 8 shows that for commercial auto liability, the average loss reserve per outstanding insurance claim has remained constant around $30,000 until 2018, after which it starts to increase and almost doubles by the end of 2021. On the other hand, the average loss reserve remains constant throughout the same period.

Based on these evidence from earnings calls and loss reserves, I compare the price response of insurers before 2018 to that after 2018. To mitigate potential concerns about the specificity of the 2018 cutoff, I also provide results from two alternative approaches. First, I replace the indicator denoting whether the year is post 2018 with a treatment window spanning from 2015 to 2018. Second, instead of using a binary step function to indicate treatment status, I employ the time-series data from insurers' earnings calls as a continuous treatment variable. The results provide qualitatively consistent estimates, which I detail later in Section 5.2.3.

Specification In the baseline specification, I employ a difference-in-differences (DD) estimator by comparing the pricing behavior for commercial auto liability to that for personal auto liability, before and after 2018. In essence, the commercial auto insurance lines are the "treated" group. The identification assumption is that of parallel trends: the difference in price changes between commercial and personal auto lines should have evolved similarly over time in absence of treatment. This assumption ensures that the observed differences in pricing behavior post-2018 can be attributed to the exposure to social inflation rather than pre-existing disparities in trends.

To this end, I estimate the following regression:

$$\Delta P_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t} \tag{13}$$

where i denotes the insurer, ℓ the product line, and t the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$.[21] $\Delta P_{i\ell t}$ is the average price change for insurer i in line ℓ in year t, and μ_ℓ and μ_{it} represent the product line and insurer-year fixed effects, respectively. The lagged controls—total assets, leverage, asset growth, and return on equity—are chosen based on their ability to capture various dimensions of an insurer's financial stability and performance, which could otherwise confound the relationship between social inflation and pricing behavior. Standard errors are clustered by insurer to account for correlated errors within the same insurer and by year to account for correlated errors within the same year.[22]

Results Figure 9 first shows the raw data, plotting the cumulative price changes for commercial and personal auto liability starting in 2011. Prior to 2018, the annual rate change for both lines are similar in magnitude, lending credence to the assumption that they insure similar types of risks. However, a noticeable divergence begins in 2018. Personal auto prices start to stabilize with close to zero increase in prices annually, which reflects (i) a decrease in the number of fatal crashes in 2018 and 2019 and (ii) reduced economic activities due to the COVID-19 pandemic.[23] In stark contrast, commercial auto prices continue to rise, reaching an average increase of nearly 10% per year.

[21]Recent criticisms related to bias arising from time-varying treatment effects (e.g., De Chaisemartin and dH́aultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and SantÁnna, 2021; Borusyak et al., 2021; Wooldridge, 2021; Goldsmith-Pinkham et al., 2022) do not apply in this setting, as treatment occurs simultaneously across all lines of business.

[22]Multi-way clustering relies on asymptotics that are in the number of clusters of the dimension with the fewest number of clusters (Cameron and Miller, 2015). Such dimension in my sample is year (2013–2021), which may raise concerns about the number of clusters. I alleviate this concern via two approaches. First, I re-estimate the difference-in-difference where standard errors are clustered only by insurer. Table A7 shows that the coefficient on the interaction term remains statistically significant with smaller standard errors. Second, I implement a wild cluster bootstrap suggested by Cameron and Miller (2015), which designed to improve the inference of clustered standard errors by resampling within clusters and is one of the most popular method for conducting inference in settings with few clusters (e.g., Acemoglu et al., 2011; Kosfeld and Rustagi, 2015; Meng et al., 2015). After implementing this procedure, I find that the p-value remains essentially equal to zero, providing further robustness to my findings.

[23]The annual census of motor vehicle deaths by the U.S. Department of Transportation shows that the number of deaths, crashes and motor vehicles all decreased in the years 2018 and 2019. This trend has been often attributed to the proliferation of safety features, leading to lower frequency of insurance claims (Assured Research, 2019).

Table 2 presents the results of estimating Equation (13). Column (1) shows that the coefficient on the interaction term is positive and statistically significant at the 1% level. The estimate of around 4.4 indicates that the annual rate change for commercial auto was on average 4.4 percentage points higher than the rate change for personal auto after 2018. Columns (2) shows that this estimate is robust to adding controls, and columns (3) and (4) show that this estimate is robust to adding insurer and insurer-year fixed effects. The magnitude is economically meaningful as it is equal to about 70% of the post-2018 average for commercial auto prices (See panel (b) of Table A1).

In order to test for parallel trends and study the dynamics of treatment effects, I estimate an event-study version of the DD model with indicators for distance to/from the treatment year. Specifically, I estimate the following specification:

$$\Delta P_{i\ell t} = \sum_{\tau=-4}^{-1} \beta_\tau^{pre} \left(\text{Commercial}_\ell \times \text{Post2018}_\tau\right) + \sum_{\tau=1}^{4} \beta_\tau^{post} \left(\text{Commercial}_\ell \times \text{Post2018}_\tau\right) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t} \tag{14}$$

where we now include lags and leads with respect to the treatment window. Figure 10 presents a visual implementation of this research design by plotting the estimates of β_τ^{pre} and β_τ^{post}. It shows that insurers increased the premiums for commercial auto liability well above that for personal auto liability lines, with this difference only appearing in 2018. The difference in slopes of these two product lines in any year gives the difference-in-differences estimate between these groups in that year, and the years prior to 2018 provide evidence in support of the absence of pre-trends.

The difference-in-difference estimate of social inflation's price impact may potentially understate the true effect. This is for two reasons. First, as Proposition 2 suggests, an increase in uncertainty for one product line affects the price of risk associated with the insurer, thereby affecting the pricing for other lines. As a result, if the change in the price of risk is sufficiently large, the price of personal auto liability insurance may have increased as well. Second, if insurers become more wary of extreme verdicts in personal auto lines in response to developments in commercial auto lines, they may adjust their estimate of losses, which may further affect prices in the personal auto lines as well. To the extent that both of these spillovers exist, it would imply that the difference-in-difference estimate is a lower bound on the actual price impact of social inflation.

5.2.2 Evidence from Triple-Difference Design

One potential concern with the baseline difference-in-difference estimation is that unobservable time-varying factors may have disproportionately affected one line of insurance versus the other. For example, insurers may simply be passing on increased reinsurance costs onto consumers that may be higher for commercial auto than personal auto liability. To address this concern, I estimate a triple-difference design by adding an additional dimension of cross-sectional heterogeneity in exposure to social inflation: geography.

Geographic Variation I first provide evidence that significant variation exists across states in exposure to social inflation. Panel (a) of Figure 11 shows the total sum of verdicts with corporate defendants that are greater than $25 million for the top 20 largest states. It shows that California, Florida, and Texas contribute disproportionately to the national totals. Panel (b) of Figure 11 also provides a similar ranking of states by dividing these numbers by the total premiums sold in 2014 for commercial auto liability in each state. Adjusting for the size of the market, states such as New Mexico and Louisiana are considered to be the most exposed.[24]

Specification To operationalize the triple-difference, I first measure each state's pre-2015 exposure to social inflation:

$$\text{Exposure}_s = \frac{\text{Total verdicts} \geq \$25M \text{ in state } s \text{ from 2001 to 2014}}{\text{Total premiums sold in state } s \text{ in 2014}}$$

The scaling by total premiums is necessary because insurers care about the loss per dollar coverage, and the pre-2015 cutoff ensures that the sorting variable is exogenous with respect to the surge in extreme verdicts and settlements.

This measure captures the state-specific component of extreme verdicts and settlements. First, states with a higher degree of economic activity are likely to experience more incidents requiring liability insurance, resulting in a greater number of potential legal cases. Second, differences in state laws governing third-party litigation financing and statutes of limitations influence the likelihood of accidents being taken to court. Finally, persistent differences in jury sentiment across states or the presence of legislative caps may lead to different verdict amounts, conditional on the accident being taken to court.

With this state-level measure, I then estimate the following regression:

$$\begin{aligned}\Delta P_{is\ell t} = {} & \alpha_0 + \alpha_1 \left(\text{Commercial}_\ell \times \text{Post2018}_t\right) + \alpha_2 \left(\text{Commercial}_\ell \times \text{HighExposure}_s\right) \\ & + \alpha_3 \left(\text{HighExposure}_s \times \text{Post2018}_t\right) + \beta \times \left(\text{Commercial}_\ell \times \text{HighExposure}_s \times \text{Post2018}_t\right) \\ & + \mu_s + \mu_\ell + \mu_{it} + \epsilon_{is\ell t} \qquad (15)\end{aligned}$$

where i denotes the insurer, s denotes the state, ℓ denotes the product line, and t denotes the year. As before, $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. Furthermore, $\text{HighExposure}_s = 1$ if for state s, Exposure_s is above median Exposure_s across states. Standard errors are clustered by insurer and by state.

[24]Tables A11 and A12 provide further summary statistics on the heterogeneity across geography.

Results Table 3 presents the results of estimating Equation (15) where I report the estimates of α_1 and β from the regression. Column (1) provides the estimates without any controls and with only product line and year fixed effects, while columns (2) and (3) adds controls and insurer fixed effects. Across these specifications, the estimate of β is positive and statistically significant at the 5% level with a magnitude of around 2. Column (4) shows the estimates with insurer-year fixed effects, which yields a smaller estimate of β at around 1.5. As the specification in column (4) excludes insurers whose rate filings are only observable in a single state, the reduction in the magnitude implies that single-state insurers on average tend to operate in higher exposure states.

The results from the triple-difference thus indicate that the difference in rate change between commercial and personal auto lines is about 1.5 to 2 percentage points higher in high exposure states. This magnitude is also economically significant as it is nearly two thirds of the difference in rate change for low exposure states. Overall, the triple-difference results lend further support to the role of social inflation risk in driving the rise in commercial auto liability rates.

5.2.3 Robustness Checks

I next provide robustness checks that address remaining concerns regarding the results from the three empirical designs.

Using Target Rates To supplement the main analysis, I also repeat the regressions using the "target rate" as the dependent variable, which represents the insurers' desired rate adjustments based on state-prescribed actuarial models. Because these rates are prior to any explicit regulatory interventions, it helps address potential concerns about cross-state and cross-product-line differences that may be influenced by varying levels of regulatory stringency. Table A8 provides the results for the difference-in-difference and shows that the estimates are statistically and economically significant, lending robustness to my earlier findings.

Using Treatment Window While the baseline analyses use 2018 as a cutoff year, I test the robustness of the results by expanding the treatment window from 2015 to 2018. This alleviates concerns about the sharp cutoff in the difference-in-difference estimation, which is in contrast to the gradual changes in the loss distribution faced by insurers. The empirical results under this expanded window are also robust, strengthening the validity of the baseline estimates (Table A9).

Using Continuous Treatment An alternative robustness check employs a continuous treatment measure and estimates the following regression:

$$\Delta P_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{DiscussionIntensity}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where $\text{DiscussionIntensity}_t$ quantifies the share of unique earnings calls among the top 25 insurance groups that discuss "social inflation," illustrated in panel (b) of Figure A3. This continuous measure allows for a more nuanced understanding of the treatment effect and accounts for varying intensities of discussion around social inflation over time. The results are consistent with baseline estimates, further reinforcing the robustness of the main findings (Table A10).

Large Insurers Only The potential concern in including small insurers in the analysis is that these firms often rely on external pricing agencies for rate filings (Oh et al., 2021). Given that such agencies manage filings for multiple insurers simultaneously, the outcomes for small insurers can be highly correlated. This correlation risks over-weighting similar outcomes, thereby potentially skewing the results. To address this issue, the analysis narrows its focus to insurers with net total assets greater than $1 billion, encompassing 188 insurers in the sample. In this restricted sample, both the difference-in-difference and the triple-difference estimators yield results that are consistent with those of the broader sample, thereby reinforcing the robustness of the study's findings. (Table A13).

Using Alternate Empirical Design I also present results from an alternate empirical design that abstracts away from specific structural breaks over time and instead focuses on variation across geographies. I provide further details in Appendix E and show that one additional extreme verdict of size $10M leads to an increase in total premiums by $60M. I also show that the economic magnitude of this estimate is consistent with the estimate from the difference-in-difference approach.

5.3 Interpreting the Price Response: Role of Risk Compensation

As the model indicates, social inflation impacts prices through both increasing the expected losses and increasing the risk compensation required by the insurers. In this subsection, I provide three pieces of empirical evidence suggesting that increasing risk compensation has contributed to the price increases.

First, I show that the price response to social inflation is larger insurers with weaker capital positions, consistent with risk compensation originating from financial frictions. Second, in line with the notion of risk compensation as compensating insurers, I find that underwriting profitability in commercial auto liability has increased despite increased losses, while it has stayed constant for personal auto liability. Finally, I show that insurers have nearly doubled their loss reserves after 2018, driven by an increase in the risk margin rather than an increase in expected losses. I then conclude by providing a lower bound on the proportion of price increases due to increases in risk compensation.

5.3.1 Evidence of Risk Compensation: Price Response and Financial Constraints

As summarized in Proposition 3, the risk compensation is increasing in the marginal cost of statutory capital. As a result, insurers with weaker balance sheets and less capacity to bear risk should have greater price increases if risk compensation is driving prices. On the other hand, the price response should be similar if they are driven by increases in expected losses. Given this insight, I next examine how the price response depends on insurers' balance sheet capacity (Proposition 3) by splitting the sample into more constrained vs. less constrained groups based on previous year's risk-based capital (RBC) ratios (Ge, 2022; Sen, 2023). Specifically, the more (less) constrained group consists of insurers whose previous year's RBC ratio is below (above) the cross-sectional median.

Figure 12 first shows the data by plotting the rate change differential for commercial and personal auto lines across two groups of insurers. A positive differential indicates that for a given insurer, the price change for commercial auto liability is larger than that for personal auto liability. The figure shows that the differences between the two groups remain negligible across the two groups until 2018. After 2018, however, the group of more constrained insurers demonstrate a larger price differential, sustaining this pattern until 2020. In 2021, both groups converge to a roughly 4 percentage point differential between commercial auto and personal auto prices.

To quantify the influence of financial constraints on the magnitude of the price response, I next estimate the following difference-in-difference specification, allowing for differential loadings across the two groups of insurers:

$$\begin{aligned}\Delta P_{i\ell t} = \alpha &+ \delta \times \text{Constrained}_{it} + \beta \times (\text{Commercial}_{\ell} \times \text{Post2018}_{t}) \\ &+ \gamma \times (\text{Commercial}_{\ell} \times \text{Post2018}_{t} \times \text{Constrained}_{it}) + \mu_{\ell} + \mu_{it} + \text{Controls} + \epsilon_{i\ell t} \quad (16)\end{aligned}$$

where the coefficient of interest is γ. The model predicts that γ should be positive and statistically significant. The results, presented in Table 4, indicate that the price response is approximately 1.7~3.2 percentage points larger for the more constrained insurers. The estimate suggests that the price increase for more constrained insurers is approximately 50% larger than that of the less constrained insurers, consistent with the role of financial constraint driving the risk compensation.

One concern with this result could be that more constrained insurers experienced higher losses on average and therefore increased their estimate of expected losses relative to the less constrained insurers. In the case, the cross-insurer heterogeneity in price response not only reflects differences in risk compensation but also differences in expected losses. To address this concern, I first compute the changes in losses for each insurer i in line of business ℓ in year t:

$$\Delta L_{i\ell t} = \frac{L_{i\ell t} - L_{i\ell,t-1}}{0.5L_{i\ell t} + 0.5L_{i\ell,t-1}} \tag{17}$$

and re-estimate Equation (16) using $\Delta L_{i\ell t}$ as the dependent variable.[25] Table A15 presents the results. Both estimates of β and γ are statistically not significant, indicating that the differences in realized losses are not driving the observed price responses across more and less constrained insurers. Furthermore, the point estimate of γ is negative, indicating that the constrained group of insurers in fact saw a *lower* increase in losses in commercial auto liability relative to personal auto liability. Collectively, these findings underscore the role of risk compensation as the primary driver behind the observed pricing trends.

5.3.2 Evidence of Risk Compensation: Trends in Underwriting Profitability

Analyzing trends in underwriting profitability offers a valuable lens to understand the role of risk compensation behind the insurers' price response. As Proposition 4 suggests, an increase in risk compensation would be accompanied by rising profitability, even amidst escalating losses. Conversely, if increased expected losses are the main driver, profit margins should either remain static or decline.

To test this prediction, I examine the trends in realized profitability in commercial auto liability relative to personal auto liability. Specifically, I estimate the following difference-in-difference specification:

$$R_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \epsilon_{i\ell t} \tag{18}$$

where $R_{i\ell t}$ denotes the profitability for insurer i in line ℓ in year t, defined as:

$$R_{i\ell t} = 1 - \frac{\text{Total Losses}_{i\ell t}}{\text{Total Premiums Sold}_{i\ell t}} \tag{19}$$

Table 5 presents the results where each column presents results from various combinations of fixed effects. The estimate of β is around 4.5 and statistically significant across various specifications, indicating that after 2018, profitability increased by 4.5 percentage points for commercial auto liability relative to personal auto liability.

To examine whether the differences in profitability is due to increasing profitability for commercial auto liability as opposed to decreasing profitability for personal auto liability, I next estimate the following equation for each line ℓ separately:

$$\forall \ell : R_{i\ell t} = \alpha + \beta \times \text{Post2018}_t + \mu_i + \epsilon_{i\ell t} \tag{20}$$

[25] This definition corresponds to the definition of flows following Davis and Haltiwanger (1992) and leads to a more robust definition of percentage change.

where I include insurer fixed effects μ_i to ensure that β is estimated using variation within an insurer over time, rather than variation across insurers.

Table 6 presents the results. Column (1) presents the results for commercial auto liability, which shows that the estimate of β is 1.84 and statistically significant at the 5% level. The estimate thus suggests that insurers' profitability for commercial auto liability increased by approximately 1.8 percentage points after 2018. On the other hand, column (2) shows that for personal auto liability, the estimate of β is statistically indistinguishable from zero with a negative point estimate. Thus profitability for personal auto liability has stayed constant or decreased, indicating that the results from Table 5 are driven by rising profitability for commercial auto liability. Overall, these results are consistent with the interpretation that insurers have charged a large risk compensation in commercial auto in response to social inflation. Consistent with the notion of a risk compensation, insurers are compensated for bearing the risk of social inflation on their balance sheets.

5.3.3 Evidence of Risk Compensation: Trends in Loss Reserves

Insurers are mandated to allocate sufficient reserves for future claims and benefits, which are typically set as expected losses combined with an additional risk margin (SwissRe, 2014; Progressive, 2021). As loss reserves are reported by the insurers in detail across product lines, the patterns in reserving decisions provide a useful window into the risk perceived by insurers, which the model suggests directly affects the magnitude of the risk compensation (Proposition 2).

I first provide evidence that the historical risk margin used by insurers in the 2005–2010 period can accurately forecast the loss reserves well up to 2017 but breaks down after 2018. To this end, I estimate the following regression for the period 2005 to 2010:

$$\bar{\phi}_{it} = \beta_0 + \beta \bar{V}_{i,t-1} + \epsilon_{it} \tag{21}$$

where $\bar{\phi}_{it}$ denotes the average reserve per claim for commercial auto liability set aside by insurer i in year t, and $\bar{V}_{i,t-1}$ denotes the average realized loss per claim for commercial auto liability for insurer i in year $t-1$. By estimating the risk margin β, this regression effectively approximates the insurer's reserving rule by using the latest available realized loss data, mirroring the information set that insurers have when setting reserves for the subsequent year. Using the coefficients estimated from the 2005–2010 period, I then forecast the average loss reserves in the post-2011 sample.

Figure 13 presents the results of the forecasting exercise where I plot both the forecast and the 95% confidence interval. It shows that the historical risk margin from the 2005–2010 period predicts the average loss reserves well up to 2017. However, post-2018, the forecasts start to significantly underestimate the loss reserves. By 2021, the average loss reserves are about \$80,000 per claim, while the historical reserving rule underestimates this number by nearly 40%. This divergence supports the hypothesis that insurers are augmenting their risk margins in face of growing uncertainty.

One potential concern is that the observed divergence is not solely attributable to an increase in the risk margin. It is possible that insurers revised their estimate of expected losses more significantly around 2018, altering how they form expectations based on realized losses. In this scenario, the increase in reserves may reflect this change in insurers' expectation formation rather than an additional risk margin. To address this concern, I provide in Appendix G a formal test of whether the risk margin has changed after 2018. The results show that the increase in expected losses post-2018 is likely too small in magnitude to fully account for the dramatic change in reserves during the same time period.

5.3.4 Bounding the Role of Risk Compensation

I conclude this section by establishing an upper bound on the proportion of price increases due to increases in expected losses. It is first worth noting that insurers heavily rely on historical losses to form their forward-looking expectation of losses. For instance, one of the most common methods for loss estimation employs a technique that projects future losses based on the growth rates in past losses across different accident years.

During a period where losses are rising every year (as shown in Figure 5), this dependence on historical data suggests that expected losses are likely to trail actual losses. Consequently, the change in expected losses during my sample period is likely smaller than the observed change in realized losses:

$$\frac{\Delta \mathbb{E}_t\left[L\right]}{\Delta P_t} \leq \frac{\Delta L_t}{\Delta P_t} \tag{22}$$

where the upper bound on the right hand side can be computed from the data. Computing the change in prices and losses from insurer balance sheet data and the rate changes suggests that $\Delta L_t / \Delta P_t \approx 52.7\%$. In other words, at most half of the observed price increase in commercial auto liability since 2018 can be explained by an increase in expected losses. With an additional assumption that markup has remained stable during my time period, this result implies that risk compensation is responsible for at least half of the price increases since 2018. This result further corroborates the previous evidence highlighting the role of risk compensation in driving prices.

5.4 Addressing Alternative Interpretations of the Price Response

I next address alternative interpretations of the insurers' price response. Specifically, I conduct additional empirical analyses to test three main alternative explanations – (i) markups, (ii) demand shifts, and (iii) collusion – for which I find only limited support.

Are the insurers' response driven by increases in markups? The concern about increased markup challenges the risk-based interpretation of my results. For example, insurers may be raising prices not due to increased risks but to exploit market power. (i) However, the difference-in-difference results, which show diverging trends in commercial and personal auto post-2018, mitigate this concern. Many dominant players operate in both markets, suggesting that strategies to capitalize on market power would have similar effects on both lines. (ii) Figure A8 shows that the Herfindahl–Hirschman index (HHI) has stayed relatively constant over time for both markets. If anything, personal auto insurance has a higher HHI than commercial auto. Furthermore, this level of market concentration is lower than in other sectors like manufacturing or finance, which is over 2,000 throughout my sample period (Autor et al., 2020). (iii) I re-estimate Equation (15) where I compare the price differential between commercial and personal auto liability across states with high HHI and states with low HHI. Table A18 shows the differential is not statistically significant across high and low HHI states, further diminishing the markup explanation.

Are observed price increases primarily driven by demand shifts? An alternative explanation for observed price increases might be a demand-side shift. While the comparative analysis between commercial and personal auto liability already partially addresses this, it doesn't rule out a more pronounced demand shift in one line over the other. This would also suggest an increase in equilibrium quantities.

To examine how quantities have changed over time, I use the fact that both revenues and average price increases are observed in my dataset. As a result, we can compute the annual increase in quantities for both commercial and personal auto liability as the following:

$$\Delta Q := \log\left(\frac{Q_{t+1}}{Q_t}\right) = \underbrace{\log\left(\frac{P_{t+1}Q_{t+1}}{P_tQ_t}\right)}_{\text{Average Change in Revenue}} - \underbrace{\log\left(\frac{P_{t+1}}{P_t}\right)}_{\text{Average Change in Price}} \tag{23}$$

Figure 14 shows that difference between ΔQ for commercial auto liability and ΔQ for personal auto liability. It shows that the difference is statistically indistinguishable from zero prior 2018. However, the starting in 2018 the equilibrium quantities decline much more than commercial auto liability.

I also provide a formal test by estimating the following equation:

$$\Delta Q_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t} \tag{24}$$

where $\Delta Q_{i\ell t}$ is the average change in quantities sold for insurer i in product line ℓ in year t. Table 7 shows that across various specifications, the estimate of β is around -4 p.p. and statistically significant. This estimate indicates that post-2018, equilibrium quantities fell by about 4 p.p. more for commercial auto liability than for personal auto liability. This finding thus supports the notion that the observed price increases are more likely attributed to a contraction in supply rather than an expansion in demand.

Are the insurers' response a result of collusive behavior? The hypothesis of collusive behavior among insurers might appear consistent with observed pricing patterns. Rate filings are publicly observable, and discussions of social inflation during earnings calls could signal competitors, aligning with Stigler (1964) model of collusion. Yet, this hypothesis clashes with several key aspects of my findings. (i) Markets conducive to collusion usually have few firms or feature high market concentration with a cost disadvantage to small entrants. The U.S. P&C insurance market, on the other hand, hosts over 1,000 firms and its HHI of around 300 during my sample period indicates a low level concentration (Figure A8).[26] Additionally, entry barriers into new product lines are relatively low, given existing brand recognition and capitalization. (ii) Estimating difference-in-difference specification shown in Equation (13) using the average loss reserves as the dependent variable shows that the insurers have increased their loss reserves for commercial auto liability relative to personal auto liability post 2018 (Table A14). This concurrent trends in reserving behaviors of insurers provides further evidence that the price increases are driven by material increases in risk rather than collusive behaviors. (iii) In addition, the concurrent reserving decisions in commercial auto liability reveal a growing divergence of opinion among insurers (Figure 15), a pattern that contradicts the expectation of aligned behavior under a collusive equilibrium.

5.5 Insurer Exits

When social inflation risk increases too much, it is no longer profitable for the insurer to provide coverage and therefore finds it optimal to exit the market. Exits are important to understand as they can have important implications for the market structure as well as consumer welfare. Anecdotally, notable firms have been found to withdraw from a subset of markets in response to social inflation. For example, Zurich, one of the largest insurers in the commercial auto market, in 2016 closed a portion of the long-haul trucking unit for U.S. companies in response to social inflation (Baskin, 2016).

To examine the degree to which exits have been prevalent, I focus on instances where insurers fully stop selling insurance in a given state.[27] Specifically, an exit of insurer from a given state is defined as when the insurer sold coverage for commercial auto in a previous year in the same state but not in the current year in the same state. Insurers are categorized by market share into large (>2%), medium (1%–2%), and small (<1%) groups. Panel (a) of Table 8 shows that hard exits are relatively rare and even more so among large insurers (the average

[26] According to Autor et al. (2020), the average HHI for manufacturing, utilities, finance, retail and wholesale trade are all over 2,000 between 2001 and 2019.

[27] I exclude insurers that have <0.05% market share as together they write a small fraction of total premiums but have the tendency to switch in and out of a state, which may lead to spurious findings.

yearly likelihood is 8.9 % for large vs. 21.7 (20.7)% for small (medium) insurers). The price response from Section 5.2 also suggests that insurer exits may be more pronounced in states that are more exposed to social inflation. Panel (b) of Table 8 categorizes states by exposure level: low-exposure states had no verdicts over $10 million, high-exposure states are the top 17, and medium-exposure includes the rest. Across these categories, I find no significant variation in exit patterns. Similar pattern emerges when looking at the raw number of exits rather than the exit probability (See Table A19).

Overall, insurers appear to manage social inflation risks primarily through price adjustments, rather than market exits. There could be several reasons why exits have been rare. For example, insurers may be under regulatory pressure to not terminate policies, fearing potential retaliation by regulators who sometimes respond by being overtly strict in other lines of businesses. In addition, the costs of exiting and re-entering the market may be high, such as the cost of re-applying for state licenses or re-establishing relationship with the regulators. The lack of exits also mirrors the pattern in other lines such as homeowners insurance, where insurers have also primarily responded through prices in response to increasing extreme weather events (Oh et al., 2021).

6 Implications for the Real Sector

From the perspective of the insured, the rising insurance costs have led to a significant increase in operating costs. One particular industry heavily affected by these developments is the trucking industry. For example, a survey of more than 80 motor carriers has found that insurance premium costs per mile has increased by nearly 50% from 2010 to 2020, despite lower levels of fatal crashes and injury crashes (ATRI, 2022). In response to the rising costs, the same survey also finds that firms with large fleets have resorted to self-insurance as an alternative to buying policies from the insurers. Opting for self-insurance essentially enables firms to circumvent the risk compensation levied by insurers, albeit without the advantage of diversification across a more expansive portfolio of policies. Consequently, this option becomes more appealing when self-diversification is viable, a situation more pertinent to larger firms.

At the same time, insurers have implemented initiatives designed to limit the incidence of extreme verdicts and settlements. One set of measures seeks to prevent accidents. For example, the usage of telematics – a method of monitoring vehicles by using GPS and on-board diagnostics – has become more prevalent (Kelley et al., 2018). Telematics are helpful as they have been shown to lead to safer driving patterns (Boodlal and Chiang, 2014). Corroborating this trend, ATRI (2022) finds that nearly every carrier adopted new safety technology during the 2018-2020 period.

Insurers have also engaged in activities designed to modulate the severity of verdicts and settlements, conditional on litigation. For example, Zurich Insurance has undertaken concerted efforts to influence the judicial aspect of the claims process, including the appointment of a specialized role: Head of Claims Judicial and Legislative Affairs. This role aims to exert a direct impact on judicial and legislative decisions within key U.S. jurisdictions, thereby seeking to shape the risk landscape in a manner more favorable to insurers (AM Best, 2021).

Looking forward, there is scope for insurers to respond through product innovation. One example is parametric insurance, which operates on pre-specified, objective criteria and expedites the claim settlement process by obviating the need for protracted litigation (Heim, 2021).[28] Another example could be through the securitization of insurance liabilities, which has been done in the form of catastrophe bonds and life settlements.[29] By transferring their risk to the security market, insurers can lower the risk compensation in their pricing response.

7 Conclusion

This paper provides empirical evidence on the risks and economic consequences of social inflation, a novel source of aggregate risk for the insurance sector. Unlike conventional risks tied to financial markets, catastrophes, or policyholder behavior, social inflation stems from the disruptions to the legal environment which affects the entire liability insurance landscape. I show that disruptions to the legal environment have persistently shifted the loss distribution faced by insurers, to which insurers have responded by significantly raising prices. Furthermore, heterogeneity in price response across insurers as well as trends in profitability and loss reserves show that the price response includes a significant risk compensation component, which stems from the interaction of uncertainty and financial frictions.

While the empirical results focus on a particular segment of the insurance market, they carry broader economic implications. The large price impact of social inflation extends to all other liability lines where the jury system plays an instrumental role. That the price response is driven by risk compensation also helps rationalize the large contraction in insurance supply in markets insuring climate and cyber risk. Finally, the increase in risk compensation also pertains to other financial intermediaries such as banks, which face similar capital regulation and are also sensitive to their forward-looking estimates of their liabilities.

Importantly, this paper also opens door to two promising lines of inquiry that extend beyond insurance markets. First, the surge in extreme verdicts and settlements, interacting with changing societal views of corporate responsibility, resonates with a long-standing idea that social norms shape economic behavior and market outcomes (Becker, 1957). In particular, recent research has shown that social norms can meaningfully impact financial markets by

[28] Lin and Kwon (2020) provides a comprehensive review of recent developments in parametric insurance.

[29] Life settlements are a form of securitization in which policies are sold to third parties who then continue to pay the premiums and collect the death benefit.

affecting investor choices (Hong and Kacperczyk, 2009; Pástor et al., 2021), corporation actions (Rajan et al., 2023), and regulatory decisions (Colonnelli et al., 2022). This paper shows that the uncertainty associated with extreme verdicts and settlements against corporations – a specific manifestation of shifting social norms – is a risk that is priced in financial markets.

Second, this paper opens up a new body of questions at the intersection of law and finance that highlights the uncertainty induced by a complex legal environment. In particular, there are many sources of disruptions that generate significant legal uncertainty, such as technological shifts that challenge existing frameworks (e.g., digital assets, privacy issues), evolving interpretations of fiduciary duties, and the growing influence of political pressure on legal decisions. My paper focuses a particular dimension by studying litigation and the subsequent jury decisions. Corporations, susceptible to litigation from both the shareholders and consumers, have the option to transfer some of these risks to the insurance sector. My findings highlight the limits to such risk transfer as they eventually manifest in the form of a risk compensation required by the insurers.

References

ABA (2017). Legal advertising blows past 1 billion and goes viral.

Abraham, K. S. (1976). Medical malpractice reform: A preliminary analysis. *Md. L. Rev.*, 36:489.

Abrams, D. S. and Chen, D. L. (2012). A market for justice: A first empirical look at third party litigation funding. *U. Pa. J. Bus. L.*, 15:1075.

Acemoglu, D., Cantoni, D., Johnson, S., and Robinson, J. A. (2011). The consequences of radical reform: The french revolution. *American economic review*, 101(7):3286–3307.

Acheson, G. G., Campbell, G., and Turner, J. D. (2019). Private contracting, law and finance. *The Review of Financial Studies*, 32(11):4156–4195.

Actuarial Standards Board (2011). Property/casualty unpaid claim estimates.

Adrian, T., Etula, E., and Muir, T. (2014). Financial intermediaries and the cross-section of asset returns. *The Journal of Finance*, 69(6):2557–2596.

Aiyar, S., Calomiris, C. W., and Wieladek, T. (2014). Does macro-prudential regulation leak? evidence from a uk policy experiment. *Journal of Money, Credit and Banking*, 46(s1):181–214.

AM Best (2021). Zurich north america names head of claims judicial and legislative affairs.

American Academy of Actuaries Joint RBC Task Force (2002). Comparison of the naic life, p&c and health rbc formulas.

Anderson, R. E. (2020). Behind the rise in large outlier medical malpractice verdicts. Technical report, Physicians Practice.

Anwar, S., Bayer, P., and Hjalmarsson, R. (2022). Unequal jury representation and its consequences. *American Economic Review: Insights*.

Ashcraft, A. B. (2005). Are banks really special? new evidence from the fdic-induced failure of healthy banks. *American Economic Review*, 95(5):1712–1730.

Assured Research (2019). Assured comment: Hard market for private passenger auto is over. Technical report, Assured Research.

Atanassov, J. and Kim, E. H. (2009). Labor and corporate governance: International evidence from restructuring decisions. *The Journal of Finance*, 64(1):341–374.

ATRI (2022). The impact of rising insurance costs on the trucking industry. Technical report, American Transportation Research Institute.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2):645–709.

Ball, D. A. and Keenan, D. C. (2009). *Reptile - The 2009 manual of the plaintiff's revolution*. Balloon Press.

Baskin, B. (2016). Nuclear verdicts have insurers running from trucks.

Becker, B., Opp, M. M., and Saidi, F. (2022). Regulatory forbearance in the us insurance industry: The effects of removing capital requirements for an asset class. *The Review of Financial Studies*, 35(12):5438–5482.

Becker, G. S. (1957). *The economics of discrimination*. University of Chicago press.

Berndt, A., Douglas, R., Duffie, D., Ferguson, M., and Schranz, D. (2005). Measuring default risk premia from default swap rates and edfs.

Blinder, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human resources*, pages 436–455.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*.

Boodlal, L. and Chiang, K.-H. (2014). Study of the impact of a telematics system on safe and fuel-efficient driving in trucks.

Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*.

Brunnermeier, M. K. and Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421.

Callaway, B. and SantÁnna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, 225(2):200–230.

Cameron, A. C. and Miller, D. L. (2015). A practitionerś guide to cluster-robust inference. *Journal of human resources*, 50(2):317–372.

Clair, A. and Klevens, S. (2018). The widespread use of litigation finance.

Cohen, L. and Gurun, U. G. (2023). Buying the verdict. *Working Paper*.

Collin-Dufresne, P., Goldstein, R. S., and Martin, J. S. (2001). The determinants of credit spread changes. *The Journal of Finance*, 56(6):2177–2207.

Colonnelli, E., Gormsen, N. J., and McQuade, T. (2022). Selfish corporations.

Committee on Property and Liability Financial Reporting (2020). *Statements of Actuarial Opinion On Property and Casualty Loss Reserves*. American Academy of Actuaries.

Cornerstone (2021). Securities class action filings: 2020 year in review.

Cutler, D. M. (1996). Why dont markets insure long-term risk? Technical report, Citeseer.

Davis, S. J. and Haltiwanger, J. (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics*, 107(3):819–863.

De Chaisemartin, C. and dH́aultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996.

Du, W., Tepper, A., and Verdelhan, A. (2018). Deviations from covered interest rate parity. *The Journal of Finance*, 73(3):915–957.

Edelman (2022). 2022 edelman trust barometer global report.

Ellul, A., Jotikasthira, C., Kartasheva, A., Lundblad, C. T., and Wagner, W. (2022). Insurers as asset managers and systemic risk. *The Review of Financial Studies*, 35(12):5483–5534.

Ellul, A., Jotikasthira, C., and Lundblad, C. T. (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics*, 101(3):596–620.

Ellul, A., Jotikasthira, C., Lundblad, C. T., and Wang, Y. (2015). Is historical cost accounting a panacea? market stress, incentive distortions, and gains trading. *The Journal of Finance*, 70(6):2489–2538.

Epermanis, K. and Harrington, S. E. (2006). Market discipline in property/casualty insurance: Evidence from premium growth surrounding changes in financial strength ratings. *Journal of Money, Credit and Banking*, pages 1515–1544.

Etula, E. (2009). Risk appetite and commodity returns. *Unpublished working paper, Harvard University*.

Farnsworth, W., Guzior, D. F., and Malani, A. (2010). Ambiguity about ambiguity: An empirical inquiry into legal interpretation. *Journal of Legal Analysis*, 2(1):257–300.

Fernandes, N., Lel, U., and Miller, D. P. (2010). Escape from new york: The market impact of loosening disclosure requirements. *Journal of Financial Economics*, 95(2):129–147.

Foley-Fisher, N., Heinrich, N., and Verani, S. (2021). Are us life insurers the new shadow banks? *Available at SSRN 3534847*.

Foley-Fisher, N., Narajabad, B., and Verani, S. (2020). Self-fulfilling runs: Evidence from the us life insurance industry. *Journal of Political Economy*, 128(9):3520–3569.

Frese, R. C. (2021). Assessing social inflationś disruption to data, metrics, and forecasts: 10 mitigation strategies.

Froot, K. A. and O'Connell, P. G. (1999). The pricing of us catastrophe reinsurance. In *The Financing of Catastrophe Risk*, pages 195–232. University of Chicago Press.

Gabaix, X., Krishnamurthy, A., and Vigneron, O. (2007). Limits of arbitrage: Theory and evidence from the mortgage-backed securities market. *The Journal of Finance*, 62(2):557–595.

Gandhi, A., Samek, A., and Serrano-Padial, R. (2021). Uncertainty and welfare in insurance markets. *Available at SSRN 4419553*.

Ge, S. (2022). How do financial constraints affect product pricing? evidence from weather and life insurance premiums. *The Journal of Finance*, 77(1):449–503.

Ge, S. and Weisbach, M. S. (2021). The role of financial conditions in portfolio choices: The case of insurers. *Journal of Financial Economics*, 142(2):803–830.

Gennaioli, N., Porta, R. L., Lopez-de Silanes, F., and Shleifer, A. (2020). Trust and insurance contracts. Technical report, National Bureau of Economic Research.

Glaeser, E. L., La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2004). Do institutions cause growth? *Journal of Economic Growth*, 9(3):271–303.

Goldsmith-Pinkham, P., Hull, P., and Kolesár, M. (2022). Contamination bias in linear regressions. Technical report, National Bureau of Economic Research.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Gottlieb, D. and Smetters, K. (2021). Lapse-based insurance. *American Economic Review*, 111(8):2377–2416.

Gron, A. (1994). Capacity constraints and cycles in property-casualty insurance markets. *The RAND Journal of Economics*, pages 110–127.

Guardado, J. R. (2023). Prevalence of medical liability premium increases unseen since 2000s continues for fourth year in a row. *AMA Policy Research Perspectives*.

Haddad, V. and Muir, T. (2021). Do intermediaries matter for aggregate asset prices? *The Journal of Finance*, 76(6):2719–2761.

Haddad, V. and Sraer, D. (2020). The banking view of bond risk premia. *The Journal of Finance*, 75(5):2465–2502.

Haran, U., Teichman, D., and Feldman, Y. (2016). Formal and social enforcement in response to individual versus corporate transgressions. *Journal of Empirical Legal Studies*, 13(4):786–808.

Hartley, D., Paulson, A., and Rosen, R. (2017). Measuring interest rate risk in the life insurance sector: The us and the uk in hufeld.

He, Z., Kelly, B., and Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, 126(1):1–35.

He, Z. and Krishnamurthy, A. (2013). Intermediary asset pricing. *American Economic Review*, 103(2):732–770.

He, Z. and Krishnamurthy, A. (2018). Intermediary asset pricing and the financial crisis. *Annual Review of Financial Economics*, 10:173–197.

Heim, N. (2021). Social inflation: Rising tides in the insurance markets. *Working Paper*.

Hong, H. and Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of financial economics*, 93(1):15–36.

Hortaçsu, A. and Syverson, C. (2004). Product differentiation, search costs, and competition in the mutual fund industry: A case study of s&p 500 index funds. *The Quarterly journal of economics*, 119(2):403–456.

Houston, J. F. and Shan, H. (2022). Corporate esg profiles and banking relationships. *The Review of Financial Studies*, 35(7):3373–3417.

Hu, G. X., Pan, J., and Wang, J. (2013). Noise as information for illiquidity. *The Journal of Finance*, 68(6):2341–2382.

Hunter, J. R., Doroshow, J., and Heller, D. (2020). How the cash-rich insurance industry fakes crises and invents social inflation.

III (2022). Facts + statistics: Product liability.

Jung, H., Engle, R. F., Ge, S., and Zeng, X. (2023). Measuring the climate risk exposure of insurers. *FRB of New York Staff Report*, (1066).

Kaplan, S. N., Martel, F., and Stromberg, P. (2003). How do legal differences and learning affect financial contracts? *NBER Working Paper*.

Kashyap, A. K. and Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428.

Kelley, K., Fontanetta, L., Heintzman, M., and Pereira, N. (2018). Artificial intelligence: Implications for social inflation and insurance. *Risk Management and Insurance Review*.

Kempf, E. and Spalt, O. G. (2019). Litigating innovation: Evidence from securities class action lawsuits. *European Corporate Governance Institute-Finance Working Paper*, (614).

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–1442.

Klein, A. and Zur, E. (2009). Entrepreneurial shareholder activism: Hedge funds and other private investors. *The Journal of Finance*, 64(1):187–229.

Klein, K. S. (2023). The case for pausing any immediate embrace of the social inflation argument for legal system reforms. *Working Paper*.

Koijen, R. S., Lee, H. K., and Van Nieuwerburgh, S. (2022). Aggregate lapsation risk.

Koijen, R. S. and Yogo, M. (2015). The cost of financial frictions for life insurers. *American Economic Review*, 105(1):445–75.

Koijen, R. S. and Yogo, M. (2016). Shadow insurance. *Econometrica*, 84(3):1265–1287.

Koijen, R. S. and Yogo, M. (2022a). The fragility of market risk insurance. *The Journal of Finance*, 77(2):815–862.

Koijen, R. S. and Yogo, M. (2022b). Global life insurers during a low interest rate environment. In *AEA Papers and Proceedings*, volume 112, pages 503–508. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Koijen, R. S. and Yogo, M. (2023). Understanding the ownership structure of corporate bonds. *American Economic Review: Insights*, 5(1):73–91.

Kosfeld, M. and Rustagi, D. (2015). Leader punishment and cooperation in groups: Experimental field evidence from commons management in ethiopia. *American Economic Review*, 105(2):747–783.

La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2006). What works in securities laws? *The Journal of Finance*, 61(1):1–32.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. W. (1997). Legal determinants of external finance. *The Journal of Finance*, 52(3):1131–1150.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. W. (1998). Law and finance. *Journal of Political Economy*, 106(6):1113–1155.

Le, E. (2015). Setting the stage to make the insurers pay the excess verdicts. Accessed: 2010-06-16.

Lee, J., Schoenherr, D., and Starmans, J. (2022). The economics of legal uncertainty. *Working Paper*.

Lefstin, J. A. (2006). The measure of the doubt: Dissent, indeterminacy, and interpretation at the federal circuit. *Hastings LJ*, 58(1025).

Lerner, J. and Schoar, A. (2005). Does legal enforcement affect financial transactions? the contractual channel in private equity. *The Quarterly Journal of Economics*, 120(1):223–246.

Lin, X. and Kwon, W. (2020). Application of parametric insurance in principle-compliant and innovative ways. *Risk Management and Insurance Review*.

Liu, J. and Liu, W. (2023). The effect of political frictions on the pricing and supply of insurance. *The Review of Financial Studies*, page hhad073.

Loughran, D. (2019). Who will pay for the opioid epidemic?

Mello, M. M., Studdert, D. M., and Brennan, T. A. (2003). The new medical malpractice crisis. *New England Journal of Medicine*, 348(23):2281–2284.

Meng, X., Qian, N., and Yared, P. (2015). The institutional causes of chinaś great famine, 1959–1961. *The Review of Economic Studies*, 82(4):1568–1611.

Mitchell, M., Pedersen, L. H., and Pulvino, T. (2007). Slow moving capital. *American Economic Review*, 97(2):215–220.

Mitchell, M. and Pulvino, T. (2012). Arbitrage crashes and the speed of capital. *Journal of Financial Economics*, 104(3):469–490.

Morris, Mitchell; Vosicky, T. (2023). Medical professional liability trends. Technical report, Milliman.

NAIC (2023). Social inflation.

Nordman, E., Cermak, D., and McDaniel, K. (2004). Medical malpractice insurance report: A study of market conditions and potential solutions to the recent crisis. Technical report, NAIC.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International economic review*, pages 693–709.

Oh, S., Sen, I., and Tenekedjieva, A.-M. (2021). Pricing of climate risk insurance: Regulatory frictions and cross-subsidies. *Available at SSRN*.

Ozdagli, A. K. and Wang, Z. K. (2019). Interest rates and insurance company investment behavior. *Available at SSRN 3479663*.

Pain, D. (2020). Social inflation: Navigating the evolving claims environment. *The Geneva Association*.

Paravisini, D. (2008). Local bank financial constraints and firm access to external finance. *The Journal of Finance*, 63(5):2161–2193.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2):550–571.

Peek, J. and Rosengren, E. S. (1997). The international transmission of financial shocks: The case of japan. *The American Economic Review*, pages 495–505.

Progressive (2021). Report on loss reserving practices. Technical report, The Progressive Corporation.

Rajan, R., Ramella, P., and Zingales, L. (2023). What purpose do corporations purport? evidence from letters to shareholders. Technical report, National Bureau of Economic Research.

Rose, M. R., Casarez, R. S., and Gutierrez, C. M. (2018). Jury pool underrepresentation in the modern era: Evidence from federal courts. *Journal of Empirical Legal Studies*.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, 82(1):34–55.

Selvin, M. and Picus, L. (1987). *The debate over jury performance: Observations from a recent asbestos case*. Rand Corporation.

Sen, I. (2023). Regulatory limits to risk management. *The Review of Financial Studies*, 36(6):2175–2223.

Sen, I. and Humphry, D. (2018). Capital regulation and product market outcomes.

Silverman, C. (2017). Bad for your health: Lawsuit advertising implications and solutions.

Siriwardane, E. N. (2019). Limited investment capital and credit spreads. *The Journal of Finance*, 74(5):2303–2347.

Soich, R. (2019). Three rising trends in d&o insurance.

Stigler, G. J. (1964). A theory of oligopoly. *Journal of political Economy*, 72(1):44–61.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

SwissRe (2014). P&c reserve workbook.

Thomson Reuters (2022). *Current Award Trends in Personal Injury, 61st edition.* Thomson Reuters.

Tort Policy Working Group (1987). An update on the liability crisis. Report, United States Department of Justice.

Uribe, A. and Scism, L. (2020). Companies are paying a lot more to insure their directors and officers.

Werner, G. and Modlin, C. (2016). Basic ratemaking fifth edition, may 2016.

Winter, R. A. (1988). The liability crisis and the dynamics of competitive insurance markets. *Yale J. on Reg.*, 5:455.

Winter, R. A. (1991). The liability insurance market. *Journal of Economic Perspectives*, 5(3):115–136.

Wooldridge, J. M. (2021). Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators. *Available at SSRN 3906345*.

Zanjani, G. (2002). Pricing and capital allocation in catastrophe insurance. *Journal of financial economics*, 65(2):283–305.

Zingales, L. (2006). *Interim Report of the Committee on Capital Markets Regulation*, chapter Competitiveness.

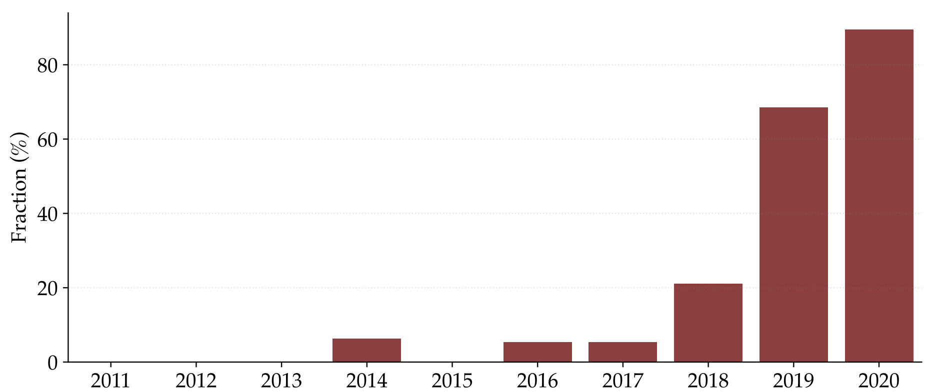


Figure 1: **Insurers' Discussion of Social Inflation**

This figure summarizes the insurers' discussion of social inflation as a source of risk for their operations. Specifically, I plot the share of top 25 insurance groups, sorted by the aggregate premiums sold in 2019, that discuss "social inflation" in their earnings conference calls. (Data Source: CapitalIQ via WRDS)

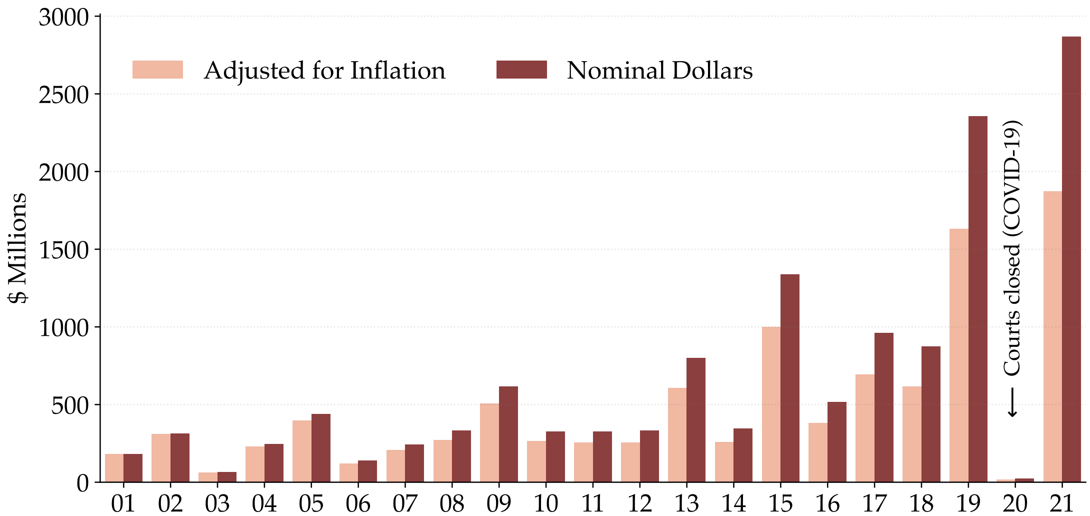


Figure 2: **Rise in Extreme Jury Verdicts**

This figure summarizes the trends in jury verdicts. I focus on personal injury cases involving motor vehicle accidents, which are incidents where individuals sustain physical harm due to others' negligent actions involving motor vehicles. Each bar represents the total sum of verdicts greater than or equal to $25 million for each year. I plot the amounts both in nominal dollars as well as those adjusted for inflation. (Data Source: VerdictSearch)

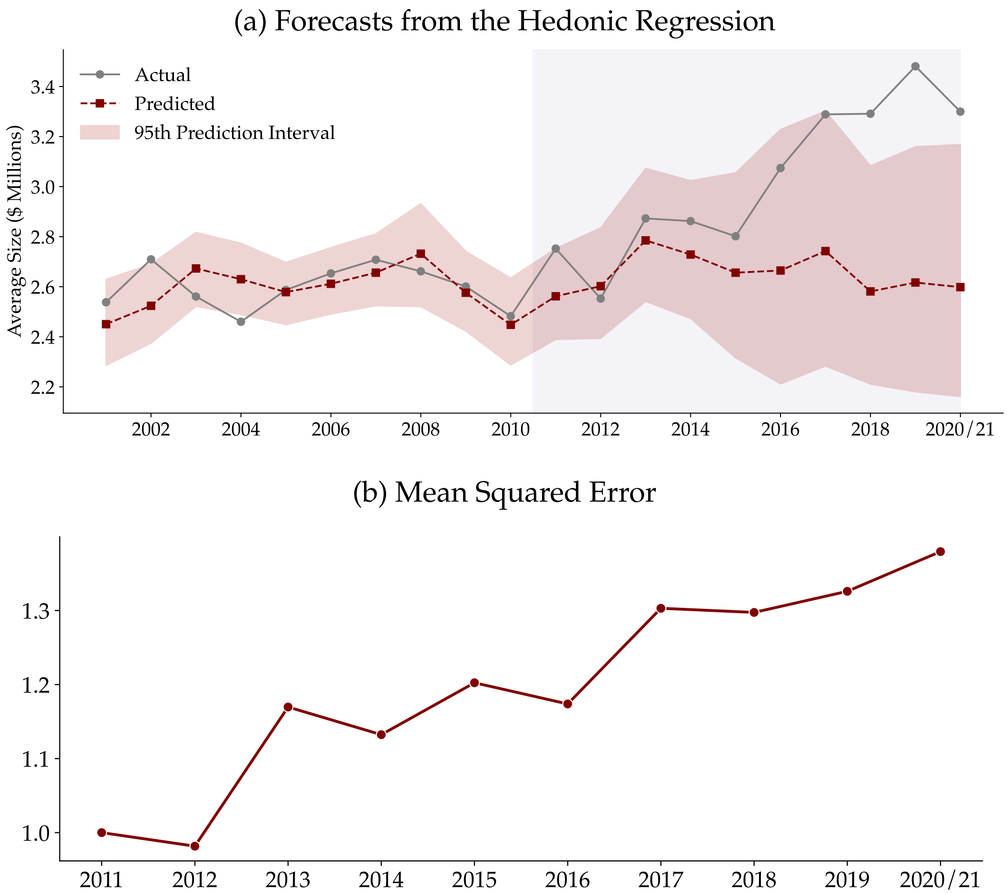


Figure 3: **Forecasting Performance of the Hedonic Model**

This figure provides the results of out-of-sample forecasts for the size of jury verdicts based on a hedonic model. The model is trained by estimating Equation (1) for a dataset of jury verdicts spanning the 2001–2010 period. Using the coefficients obtained from the model, I then construct out-of-sample forecasts for cases from 2011 and onwards, using the characteristics of each case. In panel (a), the red dotted line provides the average predicted amount with the 95% confidence interval, and the solid gray line provides the actual average in the sample. The standard errors are obtained from a bootstrapping procedure where 1,000 samples are drawn with replacement, maintaining the same number of cases for each year in the sample. Panel (b) plots the mean squared error from the out-of-sample predictions, starting in 2011. (Data Source: VerdictSearch)

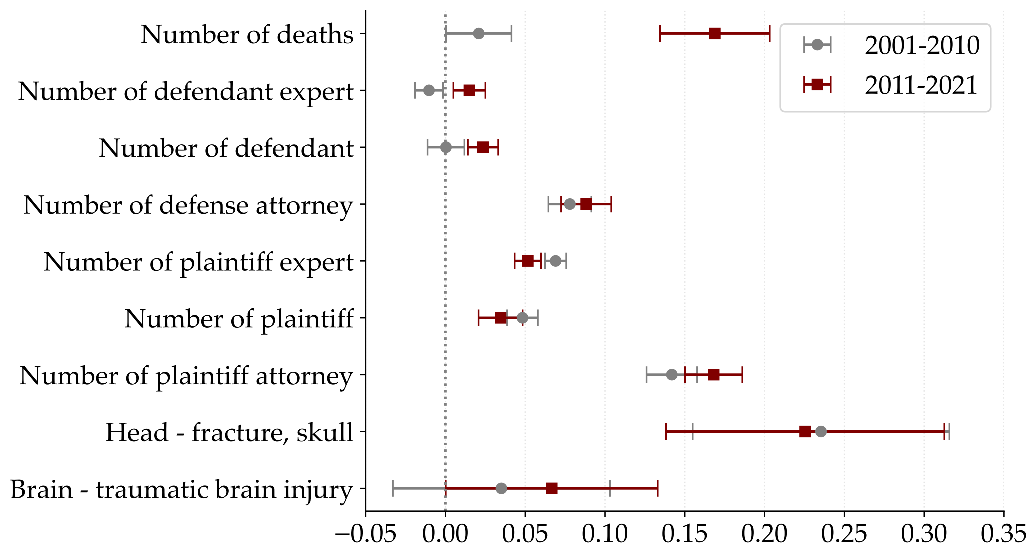


Figure 4: **Coefficients from the Hedonic Model**

This figure summarizes the coefficients from the hedonic regression by estimating Equation (1) for two separate time periods: (i) 2001–2010 period and the (ii) 2011–2021 period. Coefficients as well as the 95% confidence intervals are reported for select characteristics used in the hedonic regression. (Data Source: VerdictSearch)

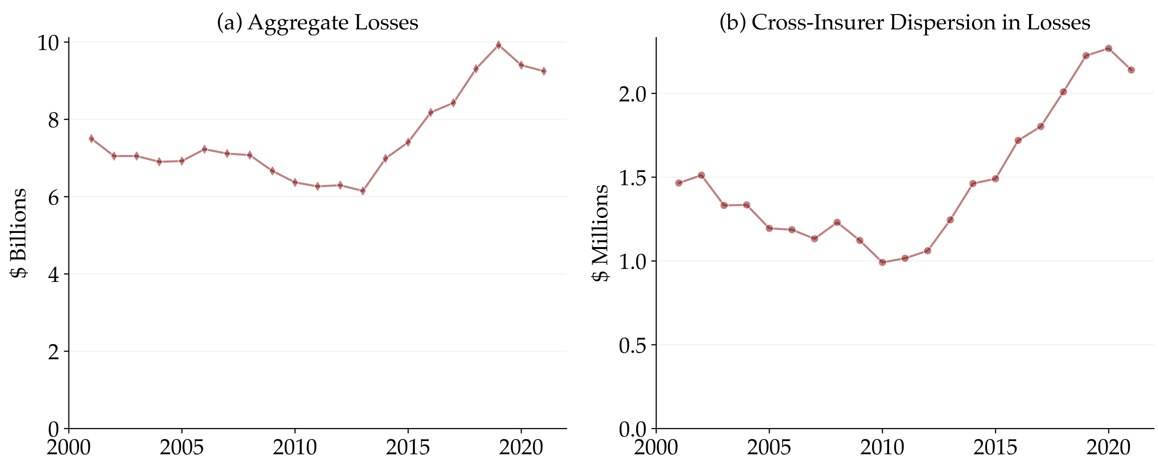


Figure 5: **Trends in Insurer Losses: Commercial Auto Liability**

This figure summarizes trends in losses for commercial auto liability. Panel (a) plots the aggregate realized losses for the entire U.S. insurance sector in commercial auto liability. Panel (b) plots the cross-insurer dispersion in realized losses in commercial auto liability, measured by the inter-quartile range across insurers in each year. Both time series are adjusted for inflation. (Data Source: S&P Global)

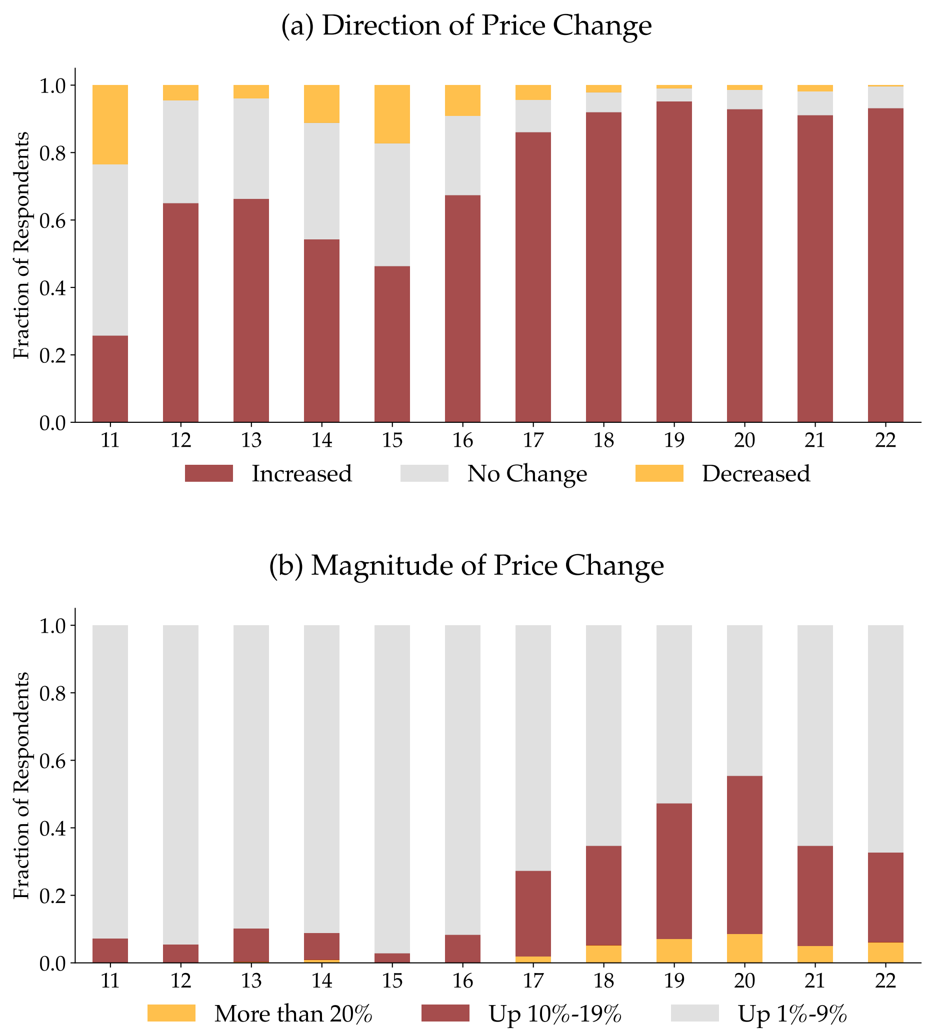


Figure 6: **Stylized Facts: Insurer Pricing Behavior**

This figure presents stylized facts on insurer pricing behavior, focusing on commercial auto liability. Panel (a) shows the proportion of commercial insurance brokers reporting an increase / no change / decrease in prices for this business line. Panel (b) summarizes the magnitude of the price change conditional on brokers reporting an increase in price. (Data Source: The Council of Insurance Agents & Brokers P/C Market Survey)

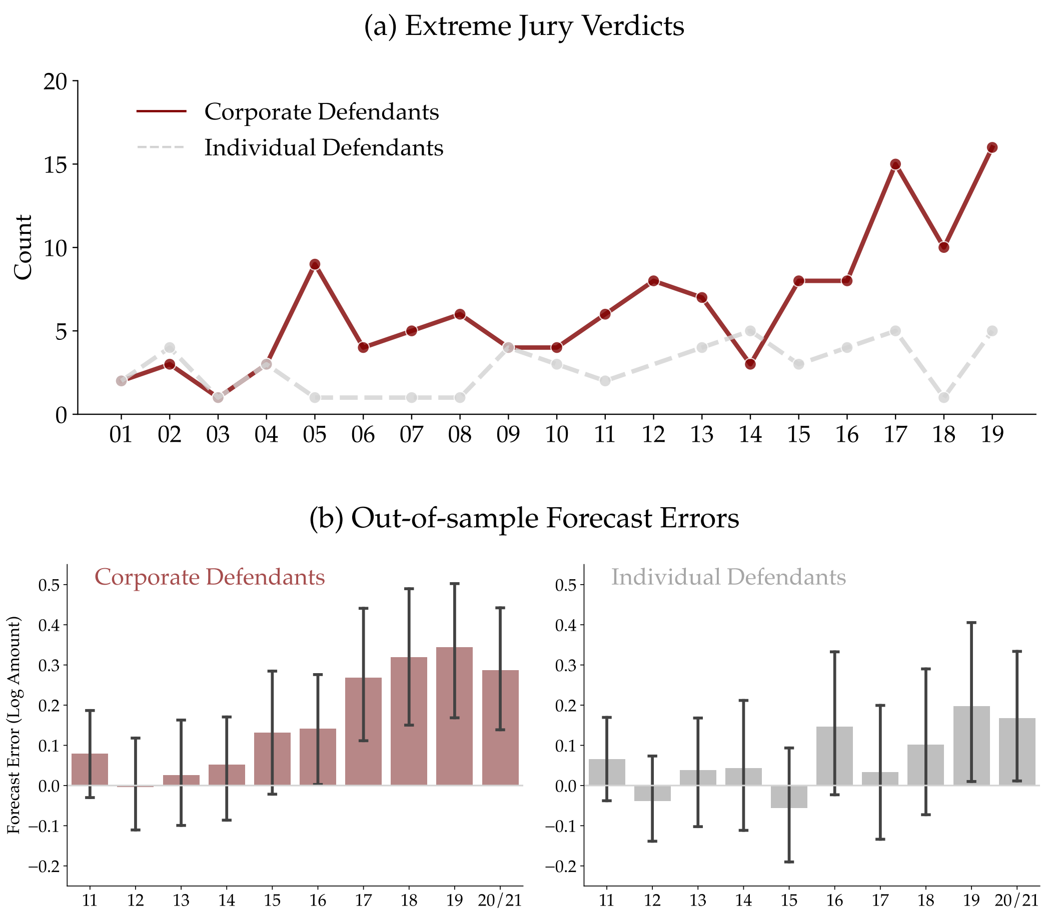


Figure 7: **Heterogeneity in Social Inflation: Lines of Business**

This figure summarizes the rise of extreme verdicts and settlements across commercial auto liability versus personal auto liability. In panel (a), I plot the total number of jury verdicts greater than $25 million in each year, separately for cases with corporate defendants and for cases with individual defendants. In panel (b), I plot the forecast errors from the out-of-sample forecast exercise described in Section 3.2. Specifically, I estimate a hedonic model for the 2001–2010 period and construct out-of-sample forecasts for cases from 2011 and onwards, using the characteristics of each case. I plot the forecast errors separately for cases with corporate defendants and for cases with individual defendants. (Data Source: VerdictSearch)

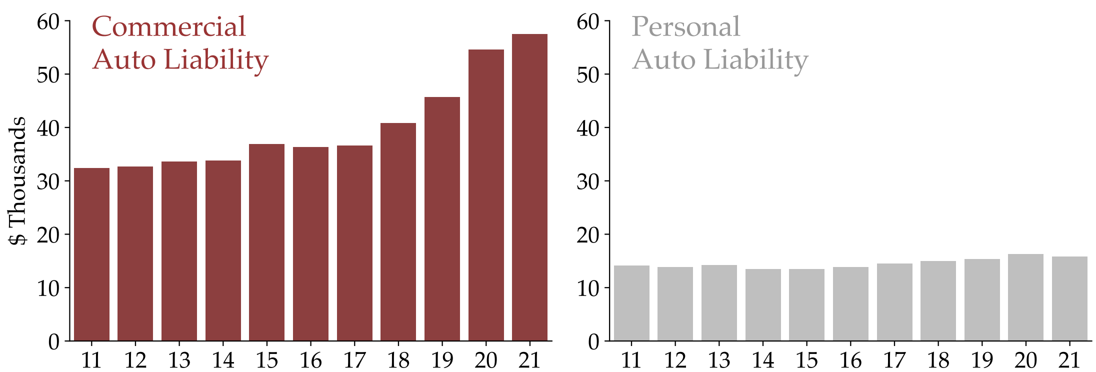


Figure 8: **Trends in Average Loss Reserves**

This figure summarizes the trends in loss reserves for commercial auto liability and for personal auto liability. Specifically, for each line of business, I divide the industry-wide total loss reserves by the total industry-wide number of outstanding insurance claims. The total industry-wide numbers are obtained by aggregating the numbers across all insurers in my sample. (Data Source: S&P Global)

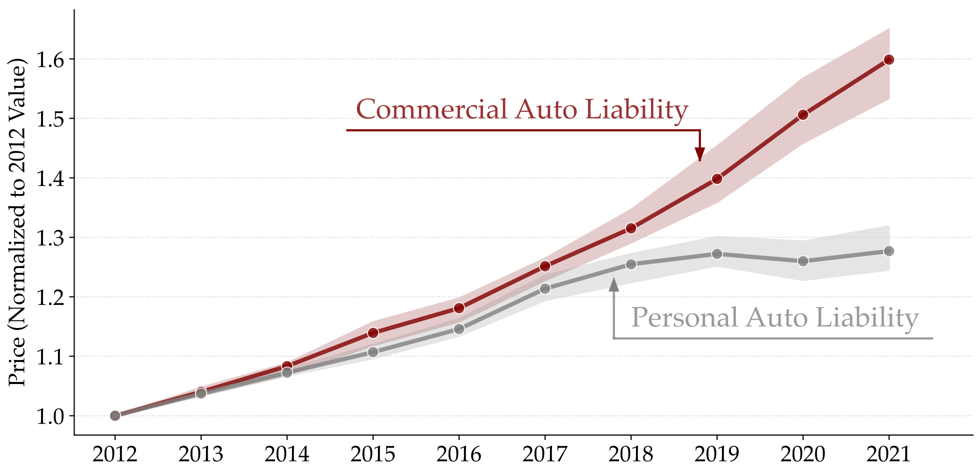


Figure 9: **Average Prices: Commercial vs. Personal Auto Liability**

This figure plots the average prices for commercial and personal auto liability, normalized to the 2012 value. For a given insurer in a given year, I first compute the annual rate change as the weighted average across all rate filings in a given year, where the weights are the amount of premiums to which the rate change applies as reported in the rate filing. I then construct a price index for each insurer starting in 2012. The solid lines represents the average price index across insurers and the confidence bands represent the 95% confidence interval around the cross-sectional mean. (Data Source: S&P Global)

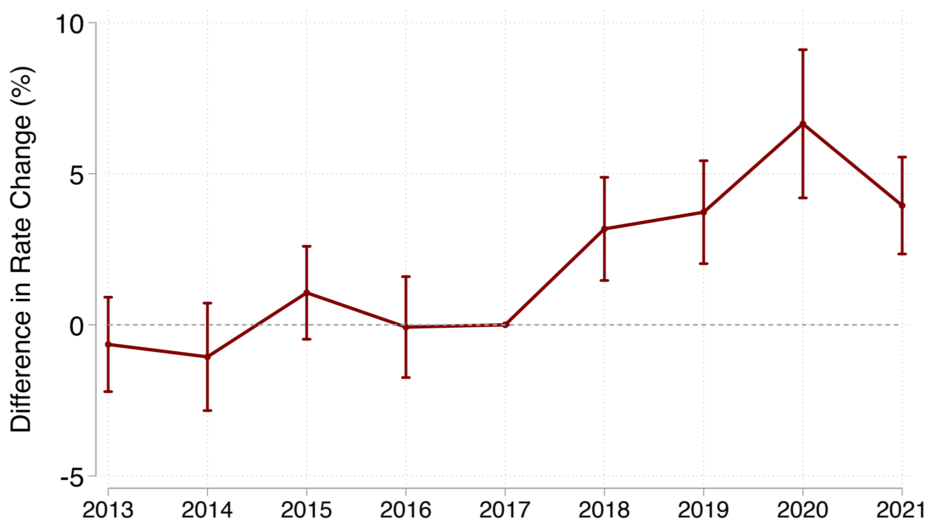


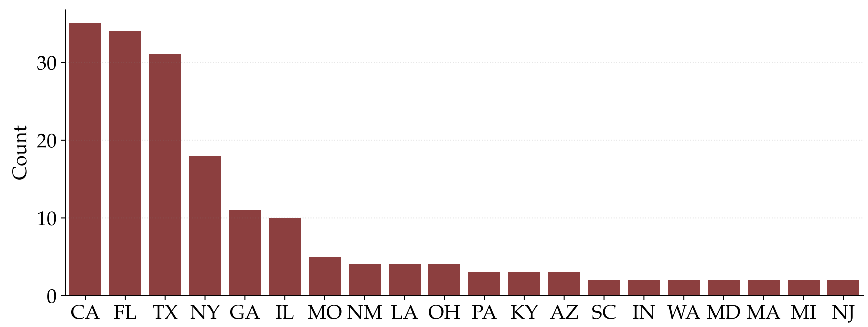
Figure 10: **Dynamics of the Insurers' Price Response**

This figure shows the dynamics of pricing response of insurers to social inflation. Specifically I estimate Equation (14):

$$\Delta P_{i\ell t} = \sum_{\tau=-4}^{-1} \beta_\tau^{pre} \left(\text{Commercial}_\ell \times \text{Post2018}_\tau\right) + \sum_{\tau=1}^{4} \beta_\tau^{post} \left(\text{Commercial}_\ell \times \text{Post2018}_\tau\right)$$
$$+ \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t denotes the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. $\Delta P_{i\ell t}$ is the average annual rate change, which is the premium-weighted average across all rate filings in a given year. μ_ℓ and μ_{it} represent the product line and insurer-year fixed effects, respectively. The lagged controls are total assets, leverage, asset growth, and return on equity. The figure plots β_τ^{pre} and β_τ^{post} relative to the 2017 baseline year, and the error bars represent the 95% confidence interval.

(a) Number of Jury Verdicts $\geq$ \$25M



(b) Amount of Jury Verdicts per \$1 Premium

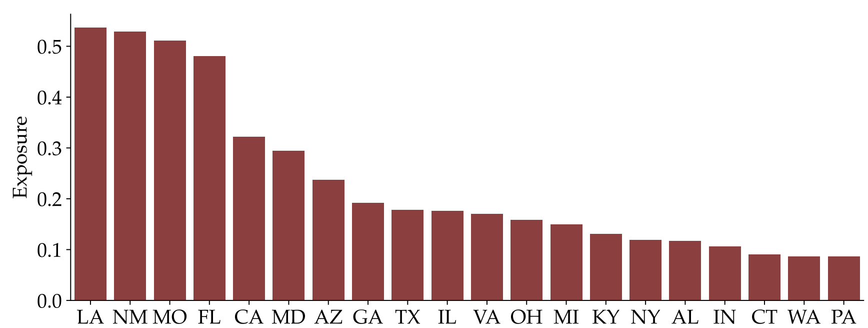


Figure 11: **Heterogeneity in Social Inflation: Geography**

This figure summarizes the rise of extreme verdicts and settlements with corporate defendants across geography. In panel (a), I plot the total sum of jury verdicts $\geq$ \$25 million in my sample for the top 20 states. In panel (b), I plot the total sum of jury verdicts $\geq$ \$25 million in my sample from 2001 to 2014, divided by the total premiums sold in 2014 for commercial auto liability in each state. (Data Source: VerdictSearch)

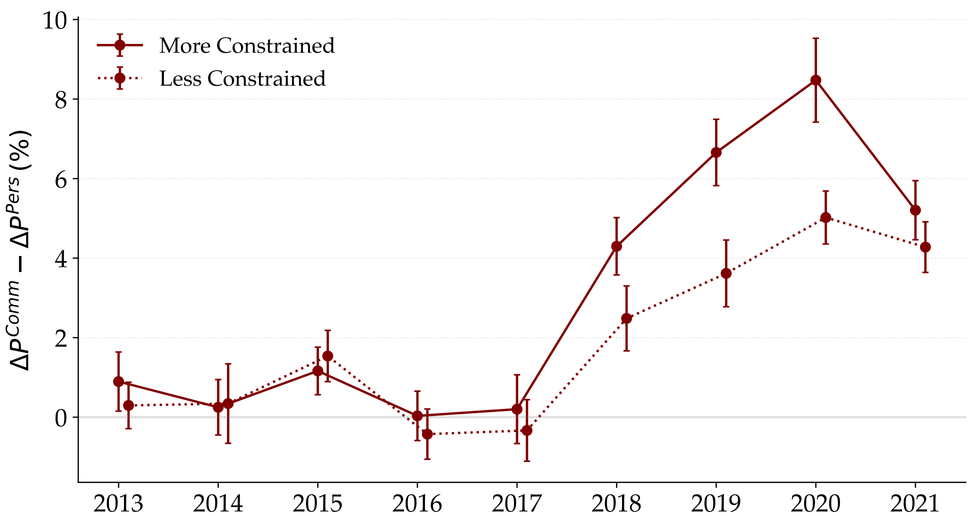


Figure 12: **Price Response and Financial Constraints**

The figure compares the difference in rate changes between commercial and personal auto lines for two groups of insurers. I calculate each insurer's annual rate change in both lines, using a premium-weighted average across all rate filings. The within-insurer rate change difference is then computed. The figure plots these average differences, along with the standard errors, for two groups: more constrained vs. less constrained insurers. Specifically, the more(less) constrained group consists of insurers whose lagged risk-based capital ratio is below(above) the cross-sectional median. (Data Source: S&P Global)

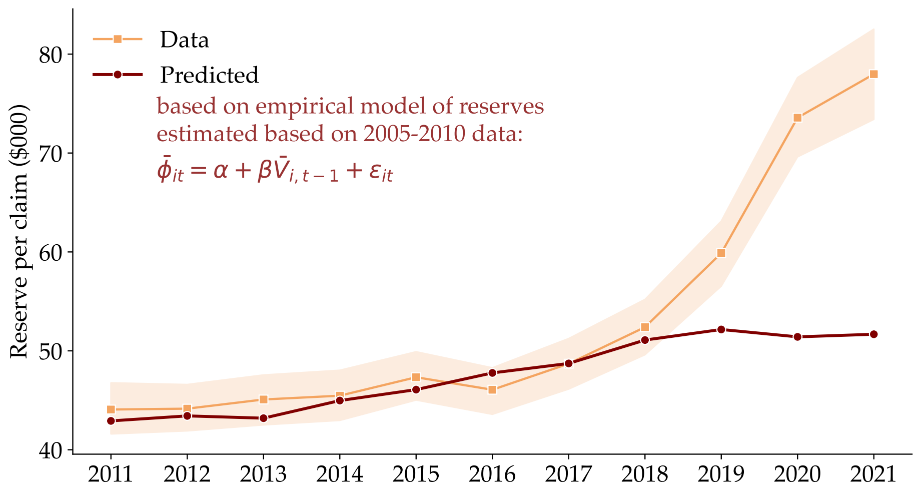


Figure 13: **Increased Risk Margins in Loss Reserves**

This figure summarizes the trends in reserving decisions for commercial auto liability. Specifically, I estimate Equation (21) for the 2001–2010 period:

$$\bar{\phi}_{it} = \beta_0 + \beta \bar{V}_{i,\text{t-1}} + \epsilon_{it}$$

where $\bar{\phi}_{it}$ denotes the average reserve per claim for commercial auto liability set aside by insurer i in year t and $\bar{V}_{i,t-1}$ denotes the average realized loss per claim for commercial auto liability for insurer i in year $t-1$. Using the coefficients obtained from the model, I then construct out-of-sample forecasts for reserves from 2011 and onwards. The red line provides the average predicted reserves with the 95% confidence interval, and the yellow line provides the actual average in the sample. (Data Source: S&P Global)

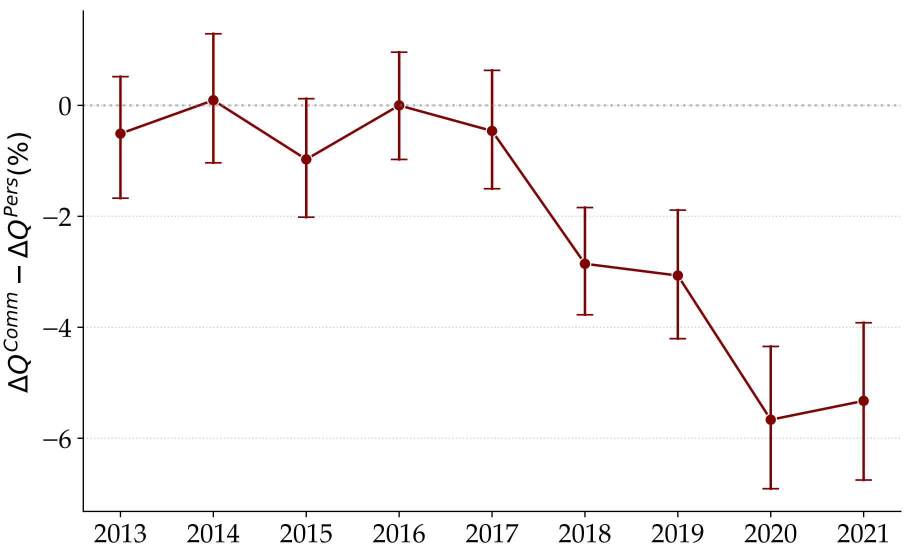


Figure 14: **Quantity Change: Commercial vs. Personal Auto Liability**

This figure plots the trends in annual quantity changes across commercial and personal auto liability. For each insurer and product line, annual quantity change is derived by subtracting the average rate change from the annual growth in revenue. I then compute the within-insurer difference across the two lines and plot the averages over time. The error bars represent the 95th confidence interval. (Data Source: S&P Global)

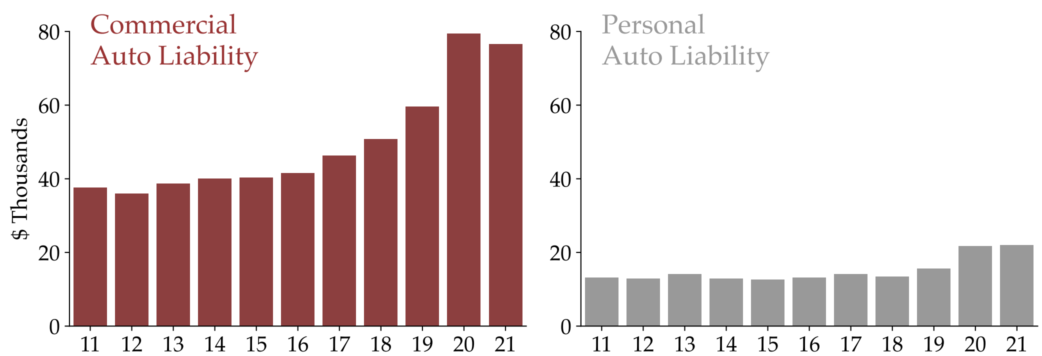


Figure 15: **Trends in Cross-Insurer Disagreement**

This figure summarizes the trends in cross-insurer dispersion in the loss reserving behavior of insurers. For each insurer in my sample and for each line of business, I compute the average reserve per claim, i.e., the aggregate amount of reserves in commercial auto liability divided by the total number of outstanding insurance claims. I then compute the cross-sectional dispersion, as measured by inter-quartile range, across insurers in the average reserve per claim for each year. I plot the time-series for commercial auto liability and personal auto liability. (Data Source: S&P Global)

Table 1: **Insurers and Extreme Verdicts and Settlements**

This table summarizes the frequency and total value of verdicts and settlements exceeding $10 million, categorizing them by the insurance groups associated with each case. For each case, I read through the case descriptions and identify the relevant insurance group. The table shows both the total count and the aggregate monetary amount for these cases, focusing on the top 15 insurance groups in the sample. (Data Source: VerdictSearch)

Insurance Group	Count	Amount ($ Million)
State Farm	380	1172.1
Allstate Corp	269	1027.5
Liberty Mutual	237	1331.2
AIG	230	2108.9
Travelers	173	606.1
Zurich	161	1195.0
Nationwide	131	478.4
Progressive	102	1000.8
Chubb	97	497.1
Farmers Insurance	80	562.0
The Hartford	70	498.9
CNA	64	241.5
Berkshire Hathaway Inc.	52	487.2
Old Republic Insurance	45	371.4
Allianz	43	263.6

Table 2: **Insurers' Price Response: Difference-in-Difference**

This table reports the results from estimating Equation (13):

$$\Delta P_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. $\Delta P_{i\ell t}$ is the average rate change for insurer i in line ℓ in year t, which is the premium-weighted average across all rate filings in a given year for line ℓ. μ_ℓ and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer and by year. From columns (1) through (4), I progressively add controls and fixed effects. (Data Source: S&P Global)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Commercial × Post	4.375***	4.473***	4.439***	4.512***
	(0.869)	(0.804)	(0.891)	(1.111)
Product Line FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Insurer FE			Yes	
Insurer-Year FE				Yes
Controls		Yes	Yes	Yes
Time Period	2013-2021	2013-2021	2013-2021	2013-2021
R2	0.0858	0.108	0.307	0.538
Observations	4397	3761	3761	3761

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: **Insurers' Price Response: Triple-Difference**

This table reports the results from estimating Equation (15):

$$\begin{aligned}\Delta P_{is\ell t} = \alpha_0 &+ \alpha_1 \left(\text{Commercial}_\ell \times \text{Post2018}_t\right) + \alpha_2 \left(\text{Commercial}_\ell \times \text{HighExposure}_s\right) \\ &+ \alpha_3 \left(\text{HighExposure}_s \times \text{Post2018}_t\right) + \beta \times \left(\text{Commercial}_\ell \times \text{HighExposure}_s \times \text{Post2018}_t\right) \\ &+ \mu_s + \mu_\ell + \mu_{it} + \epsilon_{is\ell t}\end{aligned}$$

where i denotes the insurer, s denotes the state, ℓ denotes the product line, and t denotes the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. Furthermore, $\text{HighExposure}_s = 1$ if for state s, Exposure_s is above the median value across states, where Exposure_s is computed as the total verdicts greater than \$25 million in each state from 2001 to 2014, scaled by the total premiums sold in state s in 2014. $\Delta P_{is\ell t}$ is the average annual rate change, which is the premium-weighted average across all rate filings in a given year for line ℓ in state s. μ_s, μ_ℓ and μ_{it} represent state, product line and insurer-year fixed effects, respectively. Insurer-level controls include log(assets), leverage, asset growth, and return on equity, and state-level controls include GDP growth and change in the number of truck accidents. Standard errors are clustered by insurer and by state. From columns (1) through (4), I progressively add controls and fixed effects. (Data Source: S&P Global, FRED, NHTSA)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Commercial × High Exposure × Post	2.237**	2.127**	2.083**	1.512*
	(0.842)	(0.890)	(0.892)	(0.770)
Commercial × Post	3.775***	3.908***	3.811***	3.485***
	(0.586)	(0.644)	(0.623)	(0.665)
Controls		Yes	Yes	Yes
Product Line FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Insurer FE			Yes	
Insurer-Year FE				Yes
Time Period	2013-2021	2013-2021	2013-2021	2013-2021
R2	0.120	0.128	0.254	0.461
Observations	17250	15296	15296	15296

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: **Heterogeneity in Price Response by Financial Constraints**

This table reports the results from estimating Equation (16):

$$\Delta P_{i\ell t} = \alpha + \delta \times \text{Constrained}_{it} + \beta \times (\text{Commercial}_{\ell} \times \text{Post2018}_{t}) + \gamma \times (\text{Commercial}_{\ell} \times \text{Post2018}_{t} \times \text{Constrained}_{it}) + \mu_{\ell} + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ the product line, and t the year. $\Delta P_{i\ell t}$ is the average annual rate change, which is the premium-weighted average across all rate filings in a given year for line ℓ. $\text{Commercial}_{\ell} = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_{t} = 1$ if $t \geq 2018$. $\text{Constrained}_{it} = 1$ if insurer i's risk-based capital (RBC) ratio in year $t-1$ is below the cross-sectional median in year $t-1$. μ_{ℓ} and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer and by year. From columns (1) through (4), I progressively add controls and fixed effects. (Data Source: S&P Global)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Commercial × Post × Constrained	1.644***	1.784***	1.687***	3.248*
	(0.487)	(0.365)	(0.497)	(1.582)
Commercial × Post	3.402***	3.521***	3.569***	3.328***
	(0.764)	(0.798)	(0.808)	(0.687)
Product Line FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Insurer FE			Yes	
Insurer-Year FE				Yes
Controls		Yes	Yes	Yes
Time Period	2013-2021	2013-2021	2013-2021	2013-2021
R2	0.0995	0.118	0.309	0.542
Observations	4397	3761	3761	3761

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: **Trends in Profitability: Difference-in-Difference**

This table reports the results from estimating Equation (16):

$$R_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t denotes the year. $R_{i\ell t}$ is the profitability for insurer i in line ℓ in year t, defined as the total losses divided by the total premiums sold for insurer i in line ℓ in year t. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. μ_ℓ and μ_{it} represent product line and insurer-year fixed effects, respectively. From columns (1) through (3), I progressively add fixed effects. (Data Source: S&P Global)

	(1) Profitability	(2) Profitability	(3) Profitability
Commercial × Post	4.400*	4.551**	4.484*
	(2.261)	(2.014)	(2.544)
Controls	Yes	Yes	Yes
Product Line FE	Yes	Yes	Yes
Year FE	Yes	Yes	
Insurer FE		Yes	
Insurer-Year FE			Yes
Sample	2013-2021	2013-2021	2013-2021
Time Period	0.0497	0.313	0.551
R2	9934	9934	9934

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: **Trends in Profitability: Panel Regression**

This table reports the results from estimating Equation (16):

$$\forall \ell : R_{i\ell t} = \alpha + \beta \times \text{Post2018}_t + \mu_i + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t denotes the year. $R_{i\ell t}$ is the profitability for insurer i in line ℓ in year t, defined as the total losses divided by the total premiums sold for insurer i in line ℓ in year t. μ_i represent insurer fixed effects. $\text{Post2018}_t = 1$ if $t \geq 2018$. (Data Source: S&P Global)

	(1) Profitability	(2) Profitability
Post 2018	1.840**	-2.700
	(0.722)	(1.708)
Product Line	Commercial Auto	Personal Auto
Insurer FE	Yes	Yes
Time Period	2013-2021	2013-2021
R2	0.486	0.442
Observations	5101	4833

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: **Quantity Changes: Difference-in-Difference**

This table reports the results from estimating Equation (16):

$$\Delta Q_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ the product line, and t the year. $\Delta Q_{i\ell t}$ is the average change in quantities sold for insurer i in product line ℓ in year t, which is obtained by subtracting the average change in price (obtained from rate filings) from the average change in revenue (obtained from the balance sheet information). $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. μ_ℓ and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer and by year. (Data Source: S&P Global)

	(1) Quantity Change	(2) Quantity Change	(3) Quantity Change
Commercial × Post	-4.201***	-3.955***	-3.796***
	(0.325)	(0.303)	(0.478)
Controls	Yes	Yes	Yes
Product Line FE	Yes	Yes	Yes
Year FE	Yes	Yes	
Insurer FE		Yes	
Insurer-Year FE			Yes
Time Period	2013-2021	2013-2021	2013-2021
R2	0.134	0.419	0.638
Observations	3837	3837	3837

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: **Insurer Exits**

This table reports summarizes the trends in insurer exits. I report the fraction of insurers that exit a state, defined as the total number of exits in a given state and year divided by the total number of operating insurers in the state. An exit of insurer i in state s at time t is defined as when the insurer i provides commercial auto liability coverage in state s at time $t-1$ but not at time t in the same state. To avoid spurious results, I require that the insurer was operating in years 2008–2010 and have at least 0.5% market share in any given state. Panel (a) provides summary by the size of insurers. The large insurers have more than 2% market share, and small insurers have less than 1% market share. The medium group encompasses the remaining insurers. Panel (b) provides summary by state groups. The low exposure states are the 17 states without any verdicts or settlements greater than $10 million in my sample. The high exposure states are the top 17 states, and the medium group encompasses the remaining states. (Data Source: S&P Global, VerdictSearch)

(a) Summary by Insurer Size

	All Sample	Large	Medium	Small
2011	24.9	12.3	28.1	31.0
2012	17.5	9.9	16.6	23.2
2013	16.4	7.9	18.3	21.1
2014	15.3	5.9	17.9	20.6
2015	14.8	9.8	17.6	16.6
2016	14.9	7.4	18.0	18.6
2017	17.1	7.9	13.1	27.4
2018	16.8	10.2	26.9	15.8
2019	15.9	8.6	20.8	18.8
2020	18.8	9.7	27.7	20.7
2021	19.6	7.6	26.2	25.9
2022	16.4	9.9	17.8	21.0

(b) Summary by State Group

	All Sample	High	Medium	Low
2011	24.9	26.2	25.2	23.0
2012	17.5	17.0	15.0	21.3
2013	16.4	19.5	14.8	14.7
2014	15.3	17.7	15.5	12.5
2015	14.8	17.8	12.0	14.7
2016	14.9	11.7	16.0	16.9
2017	17.1	19.2	17.4	14.4
2018	16.8	13.3	17.0	20.2
2019	15.9	15.8	15.8	16.2
2020	18.8	15.8	22.5	18.0
2021	19.6	17.7	20.1	21.2
2022	16.4	14.1	16.0	19.4

Online Appendix

for

"Social Inflation"

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A Social Inflation in Other Insurance Lines

This section summarizes social inflation in other product lines in liability insurance.

A.1 Medical Malpractice Liability

Medical malpractice liability insurance, a near $10 billion market as of 2022, covers healthcare providers against legal claims arising from patient injuries due to alleged negligence or errors in treatment. The critical nature of health outcomes, along with the court's tendency to favor patients, contribute to an increase in frequency and magnitude of claims.

In the past, the medical malpractice liability market has experienced two notable periods of financial distress. The first took place during the 1970s (Abraham, 1976), and the second occurred in the early 2000s (Mello et al., 2003; Nordman et al., 2004). Both instances were marked by an abrupt surge in the cost of claims and, subsequently, premiums. Regulatory interventions, most notably state-level caps on non-economic damages, played a crucial role in returning stability to this line of business.

The recent decade has also seen an increase in premiums and an increase in the severity of each claim. For example, Guardado (2023) finds that in the 2019–2022 period, the proportions of premiums that increased year-to-year reached highs not seen since the 2000s. This price increase has mirrored the concurrent increase in the severity of the liability claims. For example, Morris (2023) documents an increased frequency of claims above $5 million, and Anderson (2020) finds that the percentage of medical malpractice claims greater than $500,000 has increased from less than 10% in 1999 to almost 20% in 2017.

A.2 Directors and Officers Liability

Directors and Officers (D&O) insurance serves as a financial safety net for top executives, covering legal fees and other costs in cases where they're sued for alleged wrongful acts in management decisions. The insurance also indemnifies the corporation when it covers such costs for its executives. This line of insurance has several unique features that make it vulnerable to social inflation, such as complex litigation scenarios involving shareholder actions, regulatory changes.

More recently, increasing awareness of environmental, social and governance (ESG) metrics and the COVID-19 pandemic has further increased the exposure of insurers to legal actions against directors and officers. For example, Soich (2019) shows that there has been an increase in exposures to securities class action lawsuits, social issues related to gender discrimination, and cyber security threats. Furthermore, in 2019, a total of 428 new class-action securities cases were filed across U.S. state and federal courts in 2019, the highest number on record and nearly double the 1997-2018 average (Cornerstone, 2021). This trend has translated into higher insurance premiums, particularly in the U.S. and in Australia (Uribe and Scism, 2020).

A.3 Product Liability

Product liability insurance provides coverage for manufacturers, distributors, and retailers against legal claims resulting from defective or hazardous products. This insurance is notably sensitive to social inflation factors, such as public sentiment against corporations and increased punitive damages awarded by juries.

Historically, the product liability market has faced instability from large settlements and court decisions that expanded the definitions of manufacturer responsibility. It has also been subject to important legislative changes, like the Consumer Product Safety Improvement Act of 2008, which recalibrated the insurers' expectation of the losses in this line of business.

In general, product liability lines yield the highest jury awards, where the median jury award size is close to \$4 million (III, 2022). Over the past decade, the average jury award has also increased quite steeply, from approximately \$1 million in 2014 to nearly \$2.5 million in 2020 (Thomson Reuters, 2022). This escalation in jury awards is indicative of a shifting landscape, further pressurizing insurers to recalibrate premiums and underwriting criteria.

A.4 The Opioid Crisis

Casualty insurance is increasingly impacted by the opioid crisis, a declared Nationwide Public Health Emergency since 2017. The crisis involves widespread misuse of opioids, including both prescription and illegal drugs. This epidemic has led to extensive liability claims against a range of entities—manufacturers, distributors, healthcare providers, and even corporate executives—making it a systemic liability event (Loughran, 2019).

To manage this risk, insurers have started to refine underwriting standards and reassess premium structures. In addition, they have employed realistic disaster scenarios (RDS) that characterize catastrophic mass litigation events that may follow from a legal confirmation of a link between the use of a particular product or substance and harm to human health (Pain, 2020).

B Data

My paper brings together a number of datasets described here. This section provides additional details on each of the dataset, and I provide the summary statistics in Table A1.

B.1 Verdicts and Settlements

I obtain historical data on verdicts and settlements from VerdictSearch, a comprehensive database that compiles case summaries based on feedback from both plaintiffs and defendants.[30] This database provides in-depth information for each case, including the date, court,

[30] The reported verdict amounts are predominantly initial jury verdicts, subject to various revisions including remittitur to reduce excessive awards, additur to increase insufficient awards, or appellate court decisions that could uphold, reduce, or overturn the verdict. While these initial amounts may not accurately represent the final

types of injuries, involved parties, and a synopsis of the facts. For a subset of cases, the composition of the jury award and the list of insurers involved are also documented.[31]

I focus on historical verdicts and settlements from 2001 to 2021. I narrow my sample to cases involving accidents, injuries, or damages stemming from or related to motor vehicles, which typically result in personal injury claims and therefore pertain to auto liability insurance. Utilizing the defendant information in each case, I categorize them into those with a commercial defendant versus those with a personal defendant. Given that motor vehicle cases can encompass other legal issues unrelated to auto liability insurance, I exclude cases pertaining to product liability or dram shop liability claims.[32] To ensure the accuracy and reliability of my sample, I also cross-reference the data with TopVerdict.com, a platform showcasing a list of significant jury verdicts and settlements voluntarily submitted by winning attorneys.

B.2 Insurance Rates

I obtain information on insurance rates from two sources: (i) annual market survey conducted by the Council of Insurance Agents & Brokers (CIAB) and (ii) rate filings of insurers through S&P Global.

B.2.1 CIAB Market Survey

I extract information on annual rate changes from The Council of Insurance Agents & Brokers (CIAB)'s Property and Casualty Market Survey. This survey solicits information from commercial insurance brokers regarding their rate change behavior for select commercial insurance lines. Rather than observing results for each respondent individually, I observe the distribution of rate changes (e.g.,, proportion of respondents with the answer "increased 1-9%" or "Decreased 10-19%") alongside the average rate change across all respondents. The survey is highly regarded and widely cited within the insurance industry for providing market trends and fluctuations.

B.2.2 Regulatory Rate Filings

I acquire historical rate filings of insurers for calendar years 2001 to 2021 through S&P Global, which are filed separately at the line of business level (e.g., "Business Auto" or "Truckers").

financial liability borne by insurers, they are instrumental in shaping the insurer's perceived loss distribution, often necessitating immediate financial reserves. Moreover, these initial verdicts provide a real-time gauge of the case's severity, influencing strategic decisions such as whether to settle or proceed with litigation. Additionally, these figures capture public attention and are widely cited in media, affecting both consumer behavior and regulatory responses.

[31] My discussion with law librarians suggest that VerdictSearch provides a more comprehensive coverage compared to alternative sources such as Lexias or Westlaw.

[32] Dram shop liability claims are legal claims brought against establishments that serve alcohol, such as bars, taverns, or restaurants, for the damages or injuries caused by their intoxicated patrons. In many jurisdictions, dram shop laws hold these establishments responsible if they negligently serve alcohol to a visibly intoxicated person or a minor, and that person goes on to cause harm to others, such as through a drunk driving accident or assault.

Each rate filing contains a variable called "rate impact," which indicates the estimated overall percentage change in premiums resulting from a proposed rate adjustment, considering the combined effect of all proposed changes in rates such as adjustments to individual risk factors, base rates, and rating structures. These filings also provide additional information, including filing status, number of pages of the rate filing, submitted date, disposition date, and data on the total amount of written premiums affected by the proposed rate change within a specific line of insurance and state.[33]

I consolidate the rate filings filed to the yearly level by computing within-year averages. The resulting value thus represents the overall rate change in the year by the insurer for that line of business in a given state. If the insurer did not file any rate change but operated in the state based on the historical premiums information, I assume the rate change is equal to zero.

B.3 Insurers' Textual Data

I utilize two types of textual data with insurers at their source: (i) earnings conference calls of major insurers and (ii) white papers about social inflation written by insurers and other insurance-related organizations.

B.3.1 Earnings Conference Call Transcripts

I obtain transcripts of earnings conference calls of major insurance groups from S&P via CapitalIQ. Due to the nature of the earnings calls, the sample leans heavily towards public stock companies rather than mutual companies or reciprocal exchanges which typically do not host earnings calls. The transcripts are available for 83 (1108) insurance groups (companies), which collectively account for 57.2% of the direct written premiums in 2019.

B.3.2 White Papers / Reports

I compile a sample of 36 white papers and reports written on the topic of social inflation. The sample consists of 20 written by major insurers and reinsurers and 16 written by regulators, industry associations, and think tanks. Table A5 summarizes the sample of white papers and reports.

B.4 Insurers' Financial Data

I obtain historical balance sheet information of insurers from S&P Global. I also obtain data from AM Best's Insurance Reports, which contain insurers' financial strength ratings and other financial measures calculated by AM Best. Each of AM Best's reports gives insurers' most recent ratings, which can be dated before 2003. Financial variables, except ratings, are winsorized at the 1% and 99% levels.

[33] See this link for an entire list.

C Institutional Background

I next discuss how jury verdicts and settlements reflect the changing societal perceptions of corporate responsibility. I also summarize relevant details on insurer operations and regulations.

C.1 The Jury System as Conduits of Social Norms

The jury system is an integral feature of the U.S. legal system, symbolizing democratic participation in law enforcement. In civil trials, juries bear the responsibility of determining the facts of a case, and their decisions are generally respected by courts. Hence, overturning the jury's decision is very rate and often requires showing a significant error in the process or a clear deviation from accepted legal standards.

The beliefs of the jury reflect wider social norms and play a critical role in shaping verdicts and settlements. How a jury views the balance of blame between an individual and a corporation, for example, can strongly influence outcomes in cases where individual injury victims can seek compensation through lawsuits against corporate defendants. As society's attitudes towards corporate responsibility evolve, so do these jury perspectives. Examining trends in jury verdicts and settlements therefore offers valuable insights into changing social norms.

C.2 Insurer Operations and Regulations

I next describe the institutional setting related to insurer operations and regulations – specifically their (i) pricing of insurance policies, (ii) exposure to jury verdicts and settlements, and (iii) relevant financial regulations. Understanding these aspects provides insights into the environment insurers operate in and their subsequent pricing and reserving decisions.

C.2.1 Insurance Risk Modeling and Pricing

Insurers depend on advanced risk modeling techniques to estimate potential loss distributions and accurately price insurance policies. When significant and sudden changes in underlying risk occur, the accuracy of these models can be challenged. The process of setting insurance prices is often called rate-making – premiums for a given contract are calculated based on a specific rate per unit of risk exposure, thereby allowing premiums to vary for risks with differing characteristics. For instance, in commercial auto liability insurance, common exposure units include the number of vehicles, miles traveled, or company revenue.

Each state has a regulator in charge of regulating insurance companies and markets. An insurer, when seeking to change rates in a given state, must file a rate change request with the state's Department of Insurance (DOI). The regulatory examination of the filings may take over several months and the regulator may not approve the full extent of these requests. Typically, the level of scrutiny is thought to be higher for personal insurance lines relative to commercial insurance lines (Werner and Modlin, 2016).[34]

[34] See Oh et al. (2021) for the implications of rate regulation for the insurance sector.

C.2.2 Insurer Exposure to Jury Verdicts and Settlements

Injury victims can seek compensation through lawsuits when another party's negligence causes harm. In the context of a motor vehicle accident, the injured can file a lawsuit in the state where the car accident occurred or where the defendant resides (in the case of corporate defendants, the state in which the business is incorporated). Such cases may result in a settlement or a judge or jury verdict, with insurance companies partially covering the payment. Verdicts typically include compensatory damages, covering both pecuniary (e.g.,, medical expenses, lost wages) and non-pecuniary (e.g.,, pain and suffering) aspects, as well as punitive damages for particularly harmful behavior.

Under certain circumstances, insurers may face losses exceeding the maximum amount stipulated in their policies. This can occur when an attorney alleges bad faith on the part of the insurer or secures an "assignment of claims" from the defendant, subsequently pursuing legal action against the defendant's insurers for the excess verdict (Le, 2015).

C.2.3 Financial Regulation of Insurance Companies

Insurers face financial regulation to ensure their stability and ability to pay claims. All states require insurers to meet fixed minimum capital and surplus requirements, which serve as a financial buffer to protect policyholders against unforeseen losses or business downturns. They are also subject to risk-based capital (RBC) requirements that depend on each company's specific risk profile. Regulatory action may be required if an insurer's total adjusted capital falls below a specific threshold, leading to increased oversight, corrective measures, or even seizure of the company by regulators.

Statutory accounting practices require that insurers charge losses to operations in the period in which they are incurred, even though several years may pass until the final claims are actually paid. As a result, insurers must estimate the final payout, which is known as the loss reserve. To address this challenge, insurers rely on actuarial methods and historical data to estimate their future claims liabilities.

There are two key regulations and standards related to the reserves of property and casualty insurers. First is the Property and Casualty Actuarial Opinion Model Law, which requires P&C insurers to annually provide a statement of actuarial opinion (SAO) regarding their reserves. This opinion must be provided by a qualified actuary and essentially attests to the adequacy of the insurer's reserves for unpaid claims and claim adjustment expenses. Second is the Statement of Statutory Accounting Principles (SSAP) No. 55, which provides guidance on how insurers should establish these liabilities in their financial statements.

D Model

D.1 Proofs

Proof of Proposition 1 Recall that the insurer solves the following problem:

$$\max_{P_\ell} \quad \mathbb{E}\left[\sum_{\ell=1}^{L}\left(P_\ell - \tilde{V}_\ell\right) Q_\ell\right] - C\left(K\right)$$

Using the first-order condition with respect to P_ℓ, we have:

$$\left(P_\ell - \mu_\ell\right)\frac{\partial Q_\ell}{\partial P_\ell} + Q_\ell = \left(\frac{\partial C}{\partial K}\right)\left(\frac{\partial K}{\partial P_\ell}\right)$$

Using the expression for K in Equation (5):

$$\left(P_\ell - \mu_\ell\right)\frac{\partial Q_\ell}{\partial P_\ell} + Q_\ell = \left(\frac{\partial C}{\partial K}\right)\left[\left(P_\ell - (1+\kappa)\, F_\ell^{-1}\left(\alpha\right)\right)\frac{\partial Q_\ell}{\partial P_\ell} + Q_\ell\right]$$

Divide both side by $\partial Q_\ell / \partial P_\ell$ and replacing $\partial K/\partial c$ with $-c$:

$$\left(P_\ell - \mu_\ell\right) - P_\ell\frac{1}{\epsilon_\ell} = -c\left[\left(P_\ell - (1+\kappa)\, F_\ell^{-1}\left(\alpha\right)\right) - P_\ell\frac{1}{\epsilon_\ell}\right]$$

where ϵ_ℓ is the elasticity of demand for type ℓ:

$$\epsilon_\ell = \frac{\partial Q_\ell / Q_\ell}{\partial P_\ell / P_\ell}$$

Rearranging, we obtain:

$$P_\ell\left(1 - \frac{1}{\epsilon_\ell}\right)(1+c) = \mu_\ell + c\,(1+\kappa)\, F_\ell^{-1}\left(\alpha\right)$$

Solving for P_ℓ:

$$\begin{aligned}
P_\ell &= \left(1 - \frac{1}{\epsilon_\ell}\right)^{-1}\frac{\mu_\ell + c\,(1+\kappa)\, F_\ell^{-1}\left(\alpha\right)}{1+c} \\
&= \left(1 - \frac{1}{\epsilon_\ell}\right)^{-1}\frac{\mu_\ell + c\mu_\ell - c\mu_\ell + c\,(1+\kappa)\, F_\ell^{-1}\left(\alpha\right)}{1+c} \\
&= \left(1 - \frac{1}{\epsilon_\ell}\right)^{-1}\left(\mu_\ell + \frac{c\,(1+\kappa)\, F_\ell^{-1}\left(\alpha\right) - c\mu_\ell}{1+c}\right)
\end{aligned}$$

Thus,

$$P_\ell = \left(1 - \frac{1}{\epsilon_\ell}\right)^{-1} \left(\mu_\ell + \underbrace{\left[(1+\kappa)\, F_\ell^{-1}(\alpha) - \mu_\ell\right]}_{\beta_\ell} \lambda\right)$$

where we define the marginal cost of capital λ as

$$\lambda \equiv \frac{c}{1+c}.$$

□

Proof of Proposition 2 Differentiating β_ℓ with respect to σ_ℓ:

$$\begin{aligned}\frac{\partial \beta_\ell}{\partial \sigma_\ell} &= \frac{\partial}{\partial \sigma_\ell}\left[(1+\kappa)\, F_\ell^{-1}(\alpha) - \mu_\ell\right] \\ &= (1+\kappa)\,\frac{\partial F_\ell^{-1}(\alpha)}{\partial \sigma_\ell} > 0\end{aligned}$$

where the last step follows from Assumption 1.

Furthermore, differentiating λ with respect to σ_ℓ:

$$\begin{aligned}\frac{\partial \lambda}{\partial \sigma_\ell} &= \left(\frac{\partial \lambda}{\partial c}\right)\left(\frac{\partial c}{\partial \sigma_\ell}\right) \\ &= \left(\frac{\partial \lambda}{\partial c}\right)\left(\frac{\partial c}{\partial K}\right)\left(\frac{\partial K}{\partial \sigma_\ell}\right)\end{aligned}$$

Since λ is increasing in c and c is decreasing in K, it suffices to show that $\partial K / \partial \sigma_\ell < 0$. Differentiating Equation (5) with respect to σ_ℓ :

$$\begin{aligned}\frac{\partial K}{\partial \sigma_\ell} &= \frac{\partial}{\partial \sigma_\ell}\left[R_K K_0 + \sum_{\ell=1}^{L}\left(P_\ell - (1+\kappa)\, F_\ell^{-1}(\alpha)\right) Q_\ell\right] \\ &= -(1+\kappa)\left[\frac{\partial F_\ell^{-1}(\alpha)}{\partial \sigma_\ell} Q_\ell + \frac{\partial Q_\ell}{\partial \sigma_\ell} F_\ell^{-1}(\alpha)\right] < 0\end{aligned}$$

where the last step follows from Assumptions 1 and 2. And thus the proof is complete. □

Proof of Proposition 3 Taking the derivative of c with respect to K_0:

$$\frac{\partial c}{\partial K_0} = \left(\frac{\partial c}{\partial K}\right)\left(\frac{\partial K}{\partial K_0}\right) = R_K\left(\frac{\partial c}{\partial K}\right) < 0$$

where the last line follows from the convexity of C. As

$$\frac{\partial \lambda}{\partial c} = \frac{\partial}{\partial c}\left(\frac{c}{1+c}\right) = \frac{1}{(1+c)^2} > 0.$$

it immediately follows that $\partial \lambda / \partial K_0 < 0$.□

Proof of Proposition 4 Differentiating Equation (12) with respect to σ_ℓ yields:

$$\frac{\partial \mathbb{E}\left[\tilde{R}_\ell\right]}{\partial \sigma_\ell} = \frac{\mu_\ell}{\left(1-\frac{1}{\epsilon_\ell}\right)^{-1}} \frac{(\partial \beta_\ell \lambda / \partial \sigma_\ell)}{(\beta_\ell \lambda)^2} > 0$$

where the last inequality follows from the proof for Proposition 2. □

E Additional Evidence on Insurer Price Response

As a robustness, I present results from a design that abstracts away from specific structural breaks over time and instead focuses on variation across geographies.

Specification I first compute time-varying exposure to social inflation, denoted as ζ_{st}:

$$\zeta_{st} = \frac{\text{Total verdicts} \geq \$25M \text{ in state } s \text{ in year } t}{\text{Total premiums sold in state } s \text{ in year } t}$$

which is similarly constructed as Exposure$_s$ but now in each year. I then estimate the following regression:

$$\Delta P_{ist} = \gamma \Delta \zeta_{st} + \mu_s + \mu_{it} + \text{Controls} + \epsilon_{ist} \tag{A1}$$

where i denotes the year, s the state, and t the year. ΔP_{ist} is the average rate change for insurer i in state s in year t, and $\Delta \zeta_{st} = \zeta_{st} - \zeta_{s,t-1}$ represents the yearly change in the exposure. I include insurer-year fixed effects (μ_{it}) to ensure that the relevant coefficients are estimated using variation in $\Delta \zeta_{st}$ within the same insurer in the same year across states, just as in Khwaja and Mian (2008). I also include state fixed effects (μ_s) to absorb unobserved state characteristics that may affect pricing.

As before, insurer-level controls include log total assets, leverage, asset growth, and return on equity. As the identifying assumption for this panel regression is that $\Delta \zeta_{st}$ is uncorrelated with unobserved factors that contribute to prices after adding controls, I further include time-varying state-level characteristics. Specifically, I include (i) yearly changes in GDP growth, (ii) changes in the price level, and (iii) changes in the number of automobile accidents, all of which are available at the state level.

Results Table A6 presents the results. For columns (1) through (3), the exposure is constructed only using cases greater than \$10 million, while the column (4) presents an estimate of γ using cases greater than \$25 million. Across all four columns, the estimate of γ is around 6 and statistically significant at the 5% level. To interpret this estimate, consider one additional

$10M verdict in an average state. Since the average state-level premiums in 2021 is $470M, the value of $\Delta\zeta_{st}$ is equal to 10/470. Multiplying this value by 6 and then by the average state-level premiums ($470M) implies that the additional $10M verdict leads to an increase in total premiums by $60M.

The estimate from the panel regression is also consistent with the estimate from the difference-in-difference regression. In the difference-in-difference regression, multiplying the 4.4 p.p. estimate by the size of the commercial auto liability market in 2018 ($\approx$ $32 billion) suggests that policyholders have paid $1.408 billion in additional premiums every year. In the panel regression with insurer-year fixed effects, combining the estimate (≈ 6) with the average annual change in extreme verdicts ($\approx$ 246 million) suggests that policyholders have paid $1.475 billion in additional premiums every year. Altogether, both designs yield estimates of similar economic magnitude, lending further credence of the robustness of my empirical findings.

F Drivers of Social Inflation: Evidence from Textual Analysis

In this subsection, I delve deeper into the drivers of this shift in mapping through a textual analysis of industry white papers and reports written on the topic of social inflation. This is a particularly useful set of data as these documents directly discuss potential factors contributing to the rise in verdicts and settlements from an industry perspective. To this end, I first compile a sample of 36 white papers and reports, as summarized in Table A5, which includes 20 written by major insurers and reinsurers and 16 written by regulators, industry associations, and think tanks. I then manually read through each item and tabulate the factors that it considers to be driving the trends in social inflation. I classify them broadly into three groups: (i) social factors, (ii) legal factors, and (iii) economic factors.

Figure A7 summarizes the results of this analysis and highlights three main drivers. First, over 90% of the reports cite the increase in litigation funding and attorney advertising as a key driver of social inflation. Specifically, the reports refer to the growth of third-party litigation financing, a business that provides upfront financing for lawsuits in exchange for a percentage of future awards or settlements.[35] The rise in attorney advertising is also evidenced by data – in 2016, lawyers, law firms, and legal-service providers spent $770 million on television advertisements (Silverman, 2017) and nine out of the top ten paid Google keyword searches were legal terms (ABA, 2017).

Another driver cited in most of the reports is changing social norms regarding corporate responsibility. Specifically, the reports suggest the public feels corporations should be held more accountable for wrongdoings and that insurers should also bear costs since they ultimately pay out claims. Consistent with this interpretation, numerous surveys offer evidence that sentiment towards corporations and insurers may have changed over the past decade. For example, a 2022 survey of trust in major institutions revealed only 57% of respondents

[35]While the data on the growth in personal litigation finance is limited, the data on commercial litigation finance market provides an estimate of similar developments. For example, the percentage of law firms using litigation finance grew from 36% from 2013 to 2017 (Clair and Klevens, 2018). In a related study, Abrams and Chen (2012) focuses on the Australian market and finds that third-party funding corresponds to an increase in litigation and court caseloads.

trust businesses, a number that has been steadily declining from 75% in 2012 (Edelman, 2022). Additionally, a 2021 Gallup poll found only 33% of Americans rated the ethics of insurance companies as "high" or "very high."[36]

The final driver that is frequently cited is that large awards have been widely publicized and successful legal tactics have been shared across the plaintiff bar. One approach often mentioned involves subtly encouraging jurors to envision themselves in the plaintiff's situation by focusing on safety and security issues. According to proponents, plaintiffs' attorneys who use this method have secured over $7.7 billion in verdicts and settlements (Ball and Keenan (2009)). By spotlighting and disseminating effective techniques, resources and knowledge-sharing may have enabled the plaintiff bar to drive up litigation success.

Quantifying and modeling the impacts of these three drivers poses inherent difficulties given their qualitative nature. For instance, changing social attitudes and evolving legal tactics are complex dynamics that lack straightforward quantitative measures that can be tracked cleanly over time. This is consistent with insurers' reported challenges in modeling the effects of social inflation (Frese, 2021). Specifically, many insurers note limitations in solely relying on past claims data, since historical loss patterns fail to capture the impacts of emerging societal and legal shifts causing present and future social inflation.

In contrast to the factors discussed previously, changes in accident severity are not considered a major driver of rising verdicts and settlements according to the reports. This aligns with earlier descriptive evidence indicating the rise in legal outcomes is unmatched by trends in traditional determinants like accident characteristics. Other less prominent factors mentioned include shifting demographics and rising inequality, publicity surrounding mega verdicts, and evolutions in tort law.[37]

G Trends in Risk Margin in Insurer Reserves

Insurers set the loss reserves as expected losses combined with an additional risk margin. In this section, I provide a formal test of whether the risk margin applied in loss reserves has changed after the year 2018.

Denoting ϕ_t as the dollar loss reserve per policy and V_t the dollar loss per policy in year t, the insurer's reserving decision can thus be represented as:

$$\phi_t = \mathbb{E}_t \left[V_{t+1} \right] (1 + m_t) \tag{A2}$$

[36] Many major polling organizations indicate public trust and sentiment regarding ethics and social responsibility of corporations has declined measurably over the past decade. A 2016 survey by the Public Affairs Council found that only 42% of Americans had a positive view of major U.S. companies, down from 55% in 2011. A 2015 Harris poll showed that only 21% of Americans believe large corporations act in a socially responsible manner, down from 32% in 2011. Pew Research Center surveys show the percentage of U.S. adults who feel angry at corporations making too much profit increased from 50% in 2012 to 60% in 2019. A 2015 survey by PRRI found 65% of Americans believe corporations prioritize profits over the public interest, up from 53% in 2001.

[37] See Klein (2023) for an extensive discussion of the related discussion on legal reform in response to social inflation developments.

where m_t is defined as the risk margin that the insurer applies. I further express m_t as:

$$m_t = m_1 + m_2 \text{Post2018}_t$$

Therefore, the null hypothesis is that $m_2 = 0$, i.e. the risk margin in loss reserves does not change after 2018.

Now consider the following model of expected losses:

$$\mathbb{E}_t \left[V_{t+1} \right] = b_0 + b_1 V_{t-1} + b_2 \left(V_{t-1} \times \text{Post2018}_t \right) \tag{A3}$$

where I include Post2018_t to account for the possibility that the insurer's model of expected losses may have changed after 2018 as well.

Combining equations (A2) and (A3) then implies:

$$\begin{aligned}
\phi_t &= \left(b_0 + b_1 V_{t-1} + b_2 V_{t-1} \text{Post2018}_t \right) \times \left(1 + m_1 + m_2 \text{Post2018}_t \right) \\
&= b_0 \times \left(1 + m_1 + m_2 \text{Post2018}_t \right) + b_1 \times \left(1 + m_1 + m_2 \text{Post2018}_t \right) V_{t-1} \\
&\quad + b_2 \times \left(1 + m_1 + m_2 \text{Post2018}_t \right) V_{t-1} \text{Post2018}_t \\
&= b_0 \left(1 + m_1 \right) + b_0 m_2 \times \text{Post2018}_t + b_1 \left(1 + m_1 \right) \times V_{t-1} \\
&\quad + \left(b_1 m_2 + b_2 + b_2 m_1 + b_2 m_2 \right) \times V_{t-1} \text{Post2018}_t
\end{aligned}$$

Therefore, if we estimate the following two regressions:

$$V_t = b_0 + b_1 V_{t-1} + b_2 \left(V_{t-1} \times \text{Post2018}_t \right) + \epsilon_t \tag{A4}$$

$$\phi_t = c_0 + c_1 V_{t-1} + c_2 \left(V_{t-1} \times \text{Post2018}_t \right) + c_3 \text{Post2018}_t + \epsilon_t \tag{A5}$$

then the ratio of coefficients c_1 and c_2 is given as:

$$\frac{c_2}{c_1} = \frac{b_2 \left(1 + m_1 \right) + \left(b_1 + b_2 \right) m_2}{b_1 \left(1 + m_1 \right)}$$

and therefore the null hypothesis

$$\mathcal{H}_0 : \frac{b_2}{b_1} = \frac{c_2}{c_1} \tag{A6}$$

is true if and only if $m_2 = 0$. In other words, the test of equality of the ratio of the coefficients from the two regressions is equivalent a test of the null hypothesis that the risk margin in reserves has not changed after 2018.

Table A16 summarizes the empirical exercise by estimating the two regressions. First, column (1) displays the results of estimating the regression in (A4). It shows that the model of expected losses in (A4) is reasonable with a high R-squared of nearly 60%, which assuages concerns about model misspecification Second, column (2) displays the results of estimating the regression in (A5). It shows a large and statistically significant estimate of c_2 which suggests that the relationship between loss reserves and previous-year losses have changed after 2018. Finally, I test the null hypothesis $\mathcal{H}_0$ based on the estimated parameters and reject it at the 5% level, indicating that the risk margin has indeed changed after 2018.

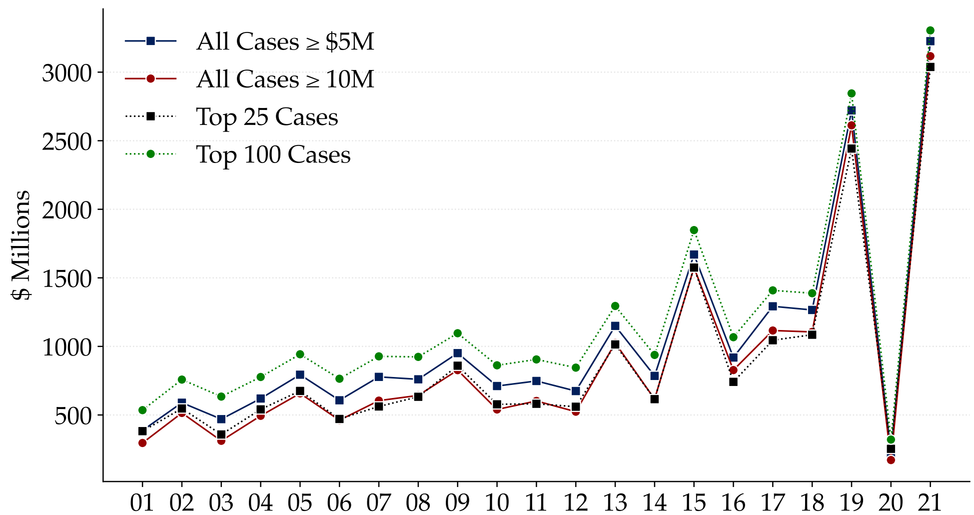


Figure A1: **Trends in Jury Verdicts and Settlements: Robustness**

This figure summarizes the trends in jury verdicts and settlements by examining different thresholds. I focus on personal injury cases involving motor vehicle accidents, which are incidents where individuals sustain physical harm due to others' negligent actions involving motor vehicles. The solid lines in blue(red) plot the total sum of verdicts and settlements greater than $5(10) million, and the dotted lines in black(green) plot the total sum of 25(100) largest verdicts and settlements in each year. (Data Source: VerdictSearch)

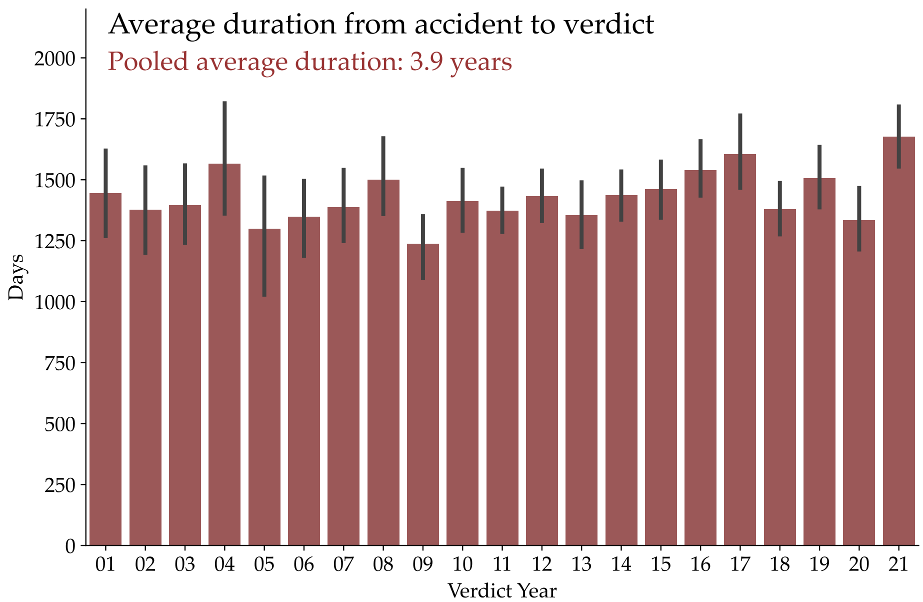
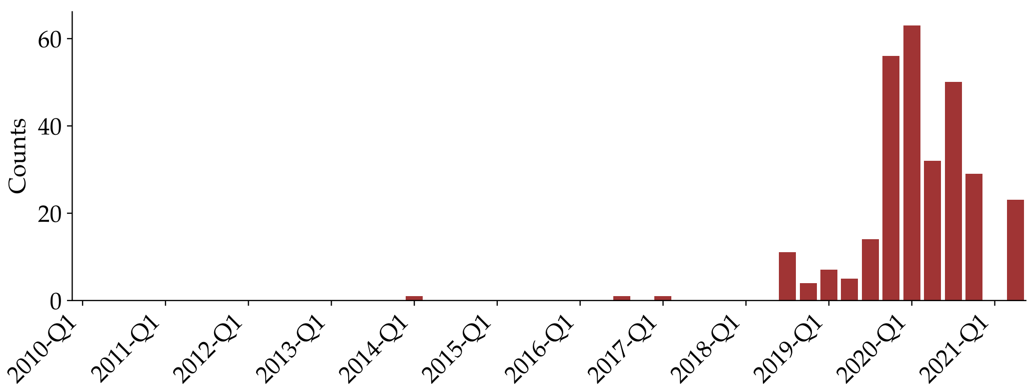


Figure A2: **Average Duration from Accidents to Jury Verdicts**

This figure summarizes the average duration of the jury verdicts in my sample. For each verdict in my sample, I first extract the date of the accident by reading the accident descriptions. I then compute the number of days that elapsed between the date of the verdict and the extracted date of the accident. For each verdict year, I plot the mean and the 95% confidence interval. I drop cases for which the exact date of the accident is not provided. (Data source: VerdictSearch)

(a) Aggregate Mentions of “Social Inflation”



(b) Share of Calls Mentioning “Social Inflation”

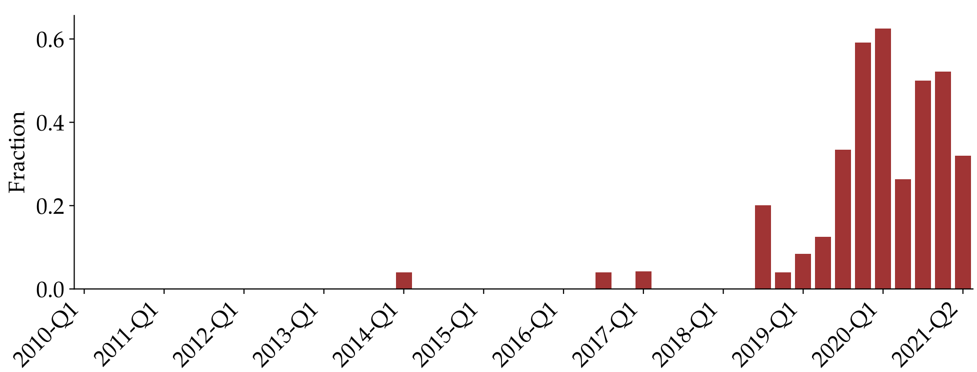


Figure A3: **Insurers’ Discussion of Social Inflation: Robustness**

This figure summarizes the insurers’ discussion of social inflation as material risk for their operations. Panel (a) plots the aggregate mentions of the term “Social Inflation” across the earnings conference calls. Panel (b) plots the share of unique earnings calls that discuss “social inflation.” Both plots are constructed focusing on the top 25 insurance groups, sorted by the aggregate premiums sold in 2019. (Data Source: CapitalIQ via WRDS)

W. R. Berkley (2018 Q2 Earnings Conference Call)

But in addition to that, we think that, as we've discussed in past quarters, it's important to give an appropriate level of consideration to social inflation. … One of the big issues around changing loss costs and inflation that comes in different flavors is the industry has not had to deal with this reality for some extended period of time. There are many professionals in the industry that have not had to operate, or during their career, they have not had to operate during an inflationary environment. Many actuaries, many underwriters, many people in other disciplines have never had to think about this as they consider what an appropriate rate is and as they think about selection.

Speaker: William Robert Berkley Jr. (President, CEO & Director)

Liberty Mutual (2021 Q4 Earnings Conference Call)

Social inflation continues to drive trends in the in the casualty lines. And I think that's where the closure of courts and some of the uncertainty still lingering post-COVID continues to drive that uncertainty.

Speaker: Neeti Bhalla Johnson (Executive VP, President of Global Risk Solutions & Director)

Travelers (2023 Q1 Earnings Conference Call)

On social inflation, just to clarify, and I think we've said it probably every quarter for the last 10 quarters, social inflation was elevated. We called it early in late 2018. We saw it in 2019. We saw it in 2020. Even during COVID when the court slowed down, we don't think social inflation has gone anywhere. So if you're thinking that social inflation is less of an issue now than it was, we don't think that, and we continue to book our loss reserves on that basis.

Speaker: Dan Frey (Executive VP and Chief Financial Officer)

Figure A4: **Anecdotal Evidence of Social Inflation: Insurer Earnings Calls**

This figure provides anecdotal evidence of social inflation based on insurers' earnings calls. (Data Source: CapitalIQ via WRDS)

The insurance industry relies on the theory of consistency when producing actuarial estimates and loss projections. This means that past loss experience is an indicative and reliable predictor of future losses. This would include losses being reported, reserved, and paid consistently over time. In addition, severity and frequency trends can be estimated and applied to historical losses in forecasting future losses. Social inflation presents a challenge to this theory by creating data that is not consistent with the past and may not behave similarly. In particular, claim patterns, claim severities, and large loss frequencies have deteriorated. This variability adds uncertainty to loss forecasts.

The impact of social inflation also brings to light the question of data reliability and quality. As long as the weaknesses and strengths of the data are understood by the user, then reasonable forecasts can still be completed. However, there may be added uncertainty. There is no doubt that social inflation has disrupted data, which adds to the complexities of using data for benchmarking, underwriting, forecasting, budgeting, and premium renewals. Some insurance companies or self-insureds may elect to account for this disruption by incorporating more conservatism and maybe even including additional contingencies.

Source: Milliman, "Assessing social inflation's disruption to data, metrics, and forecasts: 10 mitigation strategies" (September 2021)

Social inflation risks can be difficult to quantify and predict, as they are moved by "soft" social ideas and perceptions. Public distrust of large corporations, widespread use of social media, and shifting social attitudes around justice held by a changing demographic all play a role in social inflation. These non-quantitative metrics can make it challenging for insurers to accurately reserve and price products to account for potential litigation costs.

Source: NAIC, "Regulator Insight: Social Inflation" (January 2023)

Figure A5: **Anecdotal Evidence of Social Inflation: Industry Reports**

This figure provides anecdotal evidence of social inflation based on reports written by insurers and regulators. (Data Source: CapitalIQ via WRDS)

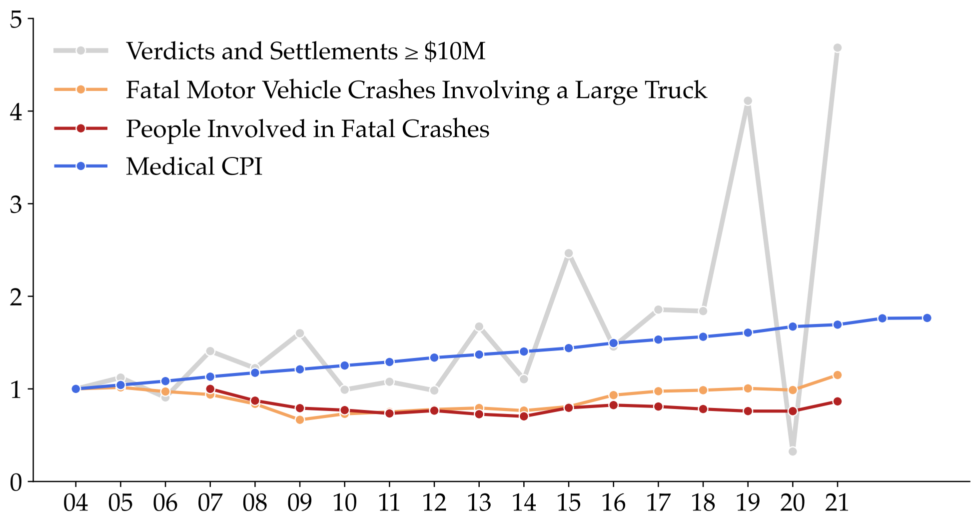


Figure A6: **Trends in Contributing Factors to Social Inflation**

This figure plots the trends in factors that may potentially contribute to trends in extreme verdicts and settlements. The gray line depicts the cumulative growth in verdicts and settlements greater than $10 million, normalized to the 2004 value. The yellow line plots the cumulative growth in the number of fatal motor vehicle crashes involving a large truck, and the blue line plots the consumer price index for medical care in U.S. cities (CPIMEDSL). The red line plots the number of people involved in fatal crashes, which is only available starting in 2007. (Data Source: VerdictSearch, National Highway Traffic Safety Administration, FRED)

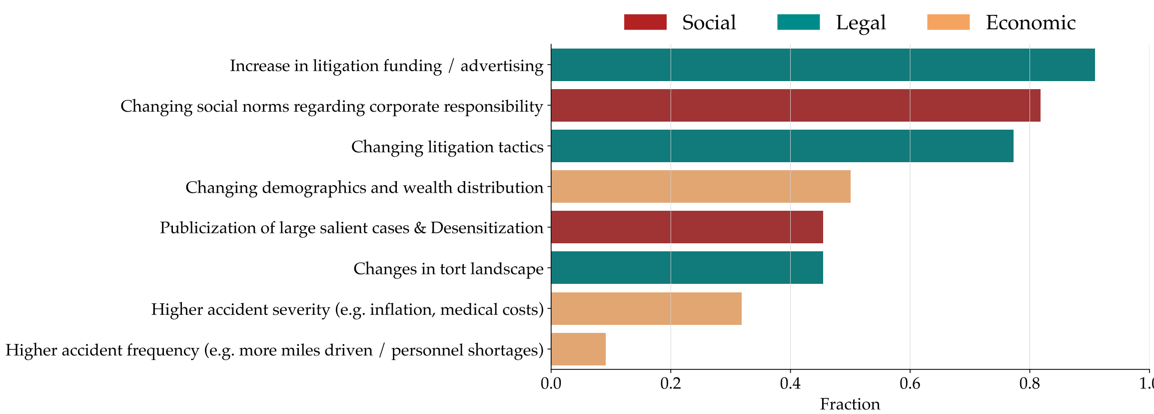


Figure A7: **Drivers of Social Inflation**

This figure summarizes the drivers of social inflation as identified by the textual analysis of industry white papers and reports written on the topic of social inflation. For each report, I manually read and tabulate the factors that it considers to be driving the trends in social inflation. I classify them broadly into three groups: (i) social factors, (ii) legal factors, and (iii) economic factors. The discussion of social factors are plotted in red; legal factors in green, and economic factors in yellow. (Data Source: Industry White Papers and Reports on Social Inflation)

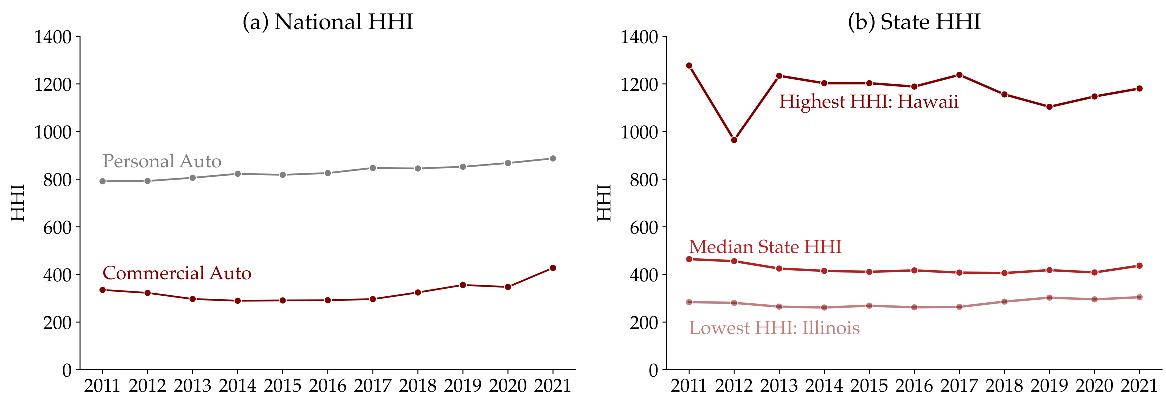


Figure A8: **HHI Trends**

This figure plots the trends in the Herfindahl-Hirschman Index (HHI) over time. In panel (a), I compute the HHI for personal auto and commercial auto separately at the national level. In panel (b), I compute the HHI for commercial auto in each state and plot the median state HHI. For reference, I also plot the trends in HHI for the states with the highest and lowest average HHI in my sample. All HHIs are calculated using insurance groups (e.g., Berkshire Hathaway) as opposed to individual companies (e.g., GEICO). (Data Source: S&P Global)

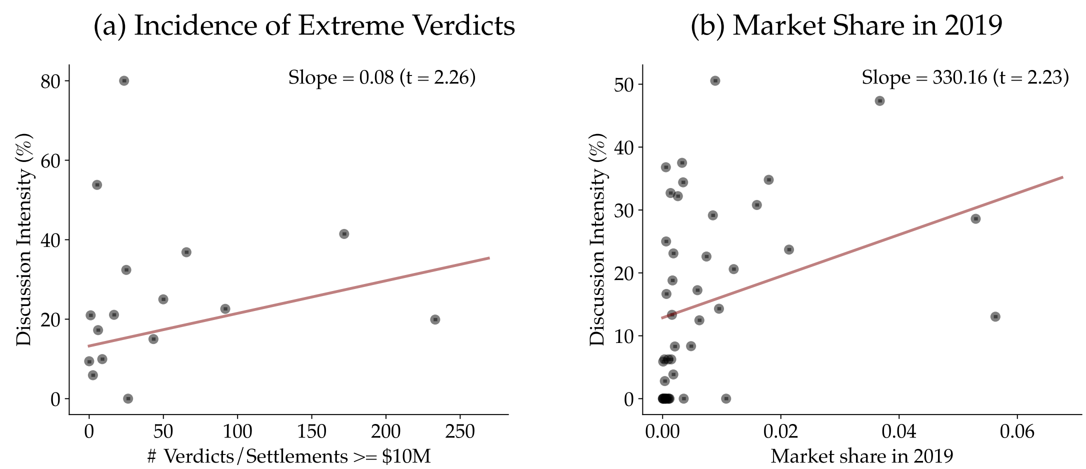


Figure A9: **Social Inflation: Heterogeneity across Insurers**

This figure examines the determinants of heterogeneity across insurers in their exposure of social inflation. Specifically, I compute for each insurer the fraction of earnings calls since 2018 that discuss social inflation, which I refer to as the discussion intensity (y-axis). In panel (a), I present a binned scatterplot against the number of verdicts and settlements that each insurer was involved with in my sample. In panel (b), I present a binned scatterplot against the market share in 2019. (Data source: VerdictSearch, CapitalIQ via WRDS)

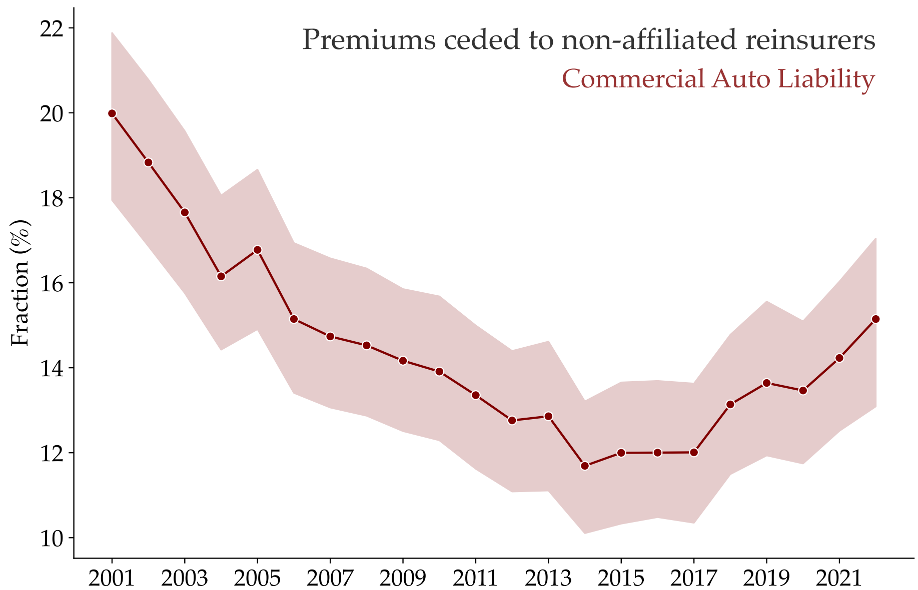


Figure A10: **Trends in Reinsurance Usage**

This figure summarizes the trends in reinsurance usage of insurers for commercial auto liability. Specifically, I compute for each insurer the fraction of direct written premiums that has been ceded to non-affiliated reinsurers (insurers outside the same insurance group). I then plot the cross-sectional mean as well as the 95% confidence interval for each year. (Data source: S&P Global)

Table A1: **Summary Statistics**

This table provides the summary statistics. Panel (a) provides the statistics for the verdicts and settlements in my sample. For each time period, I report the cross-sectional distribution of verdict and settlement amounts. Units are in $ millions. Panel (b) provides the statistics for the rate filings in my sample for commercial auto liability. For each time period, I report the cross-sectional distribution of rate changes. Units are in percentages. (Data Source: VerdictSearch)

(a) Verdicts and Settlements

Time Period	N	Mean	SD	Min	5th	25th	50th	75th	95th	Max
2001 - 2003	6414	0.83	4.53	0.00	0.00	0.01	0.07	0.40	3.31	225.00
2004 - 2006	7848	0.94	5.98	0.00	0.00	0.01	0.06	0.42	3.40	369.00
2007 - 2009	8484	0.87	4.98	0.00	0.00	0.01	0.07	0.41	3.20	330.52
2010 - 2012	7434	0.98	9.21	0.00	0.00	0.02	0.08	0.50	3.50	716.47
2013 - 2015	6624	1.15	12.38	0.00	0.00	0.02	0.07	0.38	3.50	844.57
2016 - 2018	4550	1.52	8.53	0.00	0.00	0.02	0.10	0.55	5.25	260.00
2019 - 2021	2585	3.28	35.15	0.00	0.01	0.03	0.13	0.82	7.50	1127.00

(b) Rate Change: Commercial Auto Liability

Time Period	N	Mean	SD	Min	5th	25th	50th	75th	95th	Max
2001 - 2003	239	6.33	8.45	-14.75	-4.00	2.37	5.11	9.29	21.73	44.04
2004 - 2006	633	-0.33	8.11	-24.40	-11.58	-4.60	-1.40	3.30	14.40	25.74
2007 - 2009	7947	-0.91	8.61	-27.25	-15.70	-5.00	-0.10	3.00	12.20	30.00
2010 - 2012	11833	3.40	13.48	-22.87	-12.50	-1.70	1.90	5.50	22.48	67.00
2013 - 2015	14947	5.70	7.03	-13.55	-4.40	1.80	5.00	8.80	17.80	33.80
2016 - 2018	15188	7.20	7.35	-11.81	-2.00	2.90	6.00	10.10	20.70	35.00
2019 - 2021	16022	7.37	7.89	-12.40	-3.10	2.60	6.30	10.70	21.60	37.59

Table A2: **Motivating Example for the Hedonic Regression**

This table provides a motivating example of two cases with similar accident characteristics that yielded different jury awards at two different points in time. The details of the case are taken from the accident descriptions. (Data Source: VerdictSearch)

	Example 1	Example 2
Date	March 9, 2012	June 8, 2022
Award Amount	$1,106,206	$5,000,000
Plaintiff(s)	Deborah Kropp	Anita Eisenberg
Number of Plaintiff(s)	1	1
Defendant(s)	Coca-Cola Enterprises, Inc. and Gregory Miller	Amazon.com Services, Inc. and Alfredo Mesta
Number of Defendants(s)	2	2
Case Facts	In 2007, homemaker Deborah Kropp, 51, was rear-ended by a Coca-Cola employee's truck in Gainesville, causing her car to lift into the air. She was diagnosed with strains and muscle pain initially but later asserted she suffered herniated cervical and lumbar discs and bilateral carpal tunnel syndrome, requiring multiple surgeries.	Anita Eisenberg was hit by Alfredo Mesta's truck in a parking lot on Nov. 15, 2018, causing severe injuries including a crushed knee, fractured tibia, torn meniscus, and cervical radiculopathy. Despite no surgeries, she required two months of physical therapy and continues to experience pain, including complex regional pain syndrome, affecting her ability to work.

Table A3: **Description of Insurance Product Lines**

This table summarizes the four types of auto insurance examined in the empirical analysis, differentiating their scope and target policyholders. Each type is identified by its SERFF code and brief description. (Data Source: NAIC's Uniform Property & Casualty Product Coding Matrix)

SERFF Code	Line of Business (ℓ)	Description
19.0000	Personal Auto Combinations	Coverage for a broad range of privately-owned vehicles, including SUVs and motorcycles, used for personal, non-commercial purposes.
19.0001	Private Passenger Auto (PPA)	Coverage specifically for standard passenger cars used exclusively for personal, non-commercial purposes.
20.0000	Commercial Auto Combinations	Coverage for a variety of commercial vehicles, including trucks and vans, that may be engaged in different types of business operations.
20.0001	Business Auto	Coverage specifically for vehicles used in standard business activities, excluding specialized commercial uses like garages

Table A4: **Cross-Insurer Heterogeneity in Conference Call Discussions of Social Inflation**

This table summarizes the heterogeneity across insurers in their exposure to social inflation. Specifically, I compute, for each insurer, the fraction of earnings calls since 2018 that discuss social inflation. (Data Source: CapitalIQ via WRDS)

Insurance Group	Total	Discussing Social Inflation	Discussion Intensity (%)
W. R. Berkley Corp.	20	16	80.0
Travelers	16	9	56.2
The Hartford	28	12	42.9
Tokio Marine	17	7	41.2
Chubb	13	5	38.5
Markel	15	5	33.3
CNA	13	4	30.8
Liberty Mutual	7	2	28.6
Zurich	15	4	26.7
Berkshire Hathaway Inc.	4	1	25.0

Table A5: **Sample of White Papers and Reports on Social Inflation**

This table summarizes the sample of white papers and reports written on social inflation. The sample was gathered through targeted keyword searches that include terms like "social inflation" and "nuclear verdicts." I exclude works authored by individual practitioners or law firms.

Entity Type	Number of White Papers & Reports on "Social Inflation"
Broker / Consultancy	3
Industry / Consumer Advocacy	2
P&C Insurer	16
Policy Research/Think Tank	3
Professional / Industry Association	6
Regulatory Body	2
Reinsurer / Non-U.S. Insurer	4
Total	36

Table A6: **Insurers' Price Response: Insurer-Year Fixed Effects**

This table reports the results from estimating Equation (A1):

$$\Delta P_{ist} = \gamma \Delta \zeta_{st} + \mu_s + \mu_{it} + \text{Controls} + \epsilon_{ist}$$

where i denotes the year, s denotes the state, and t denotes the year. $\Delta \zeta_{st} = \zeta_{st} - \zeta_{s,t-1}$ where ζ_{st} is the total verdicts greater than \$10 million in state s in year t, scaled by total premiums sold in state s and year t.ΔP_{ist} is the average rate change for insurer i in state s in year t, which is the premium-weighted average across all rate filings in a given year for state s. μ_s and μ_{it} represent state and insurer-year fixed effects, respectively. Insurer-level controls include log(assets), leverage, asset growth, and return on equity, and state-level controls include GDP growth, inflation, and change in the number of truck accidents. Standard errors are clustered by insurer and by state. From columns (1) through (3), I progressively add controls and fixed effects. Column (4) provides the results from constructing ζ_{st} using verdicts greater than \$25 million instead of \$10 million. (Data Source: S&P Global, FRED, NHTSA)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Change in Exposure	6.098**	5.643**	6.034***	5.514**
	(2.797)	(2.210)	(2.137)	(2.123)
Year FE	Yes	Yes		
Insurer FE		Yes		
Insurer-Year FE			Yes	Yes
Controls	Yes	Yes	Yes	Yes
Threshold	Above USD 10M	Above USD 10M	Above USD 10M	Above USD 25M
R2	0.0210	0.215	0.434	0.434
Observations	10766	10747	10460	10460

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A7: **Insurers' Price Response: Difference-in-Difference with One-way Clustering**

This table reports the results from estimating Equation (13):

$$\Delta P_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. $\Delta P_{i\ell t}$ is the average rate change for insurer i in line ℓ in year t, which is the premium-weighted average across all rate filings in a given year for line ℓ. μ_ℓ and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer, but not by year. From columns (1) through (4), I progressively add controls and fixed effects. (Data Source: S&P Global)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Commercial × Post	4.375***	4.473***	4.439***	4.512***
	(0.436)	(0.459)	(0.465)	(0.811)
Product Line FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Insurer FE			Yes	
Insurer-Year FE				Yes
Controls		Yes	Yes	Yes
Time Period	2013-2021	2013-2021	2013-2021	2013-2021
R2	0.0858	0.108	0.307	0.538
Observations	4397	3761	3761	3761

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A8: **Insurers' Price Response: Difference-in-Difference using Target Rates**

This table reports the results from estimating Equation (13):

$$\Delta P_{i\ell t} = \alpha + \beta \times (\text{Commercial}_{\ell} \times \text{Post2018}_{t}) + \mu_{\ell} + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t the year. $\text{Commercial}_{\ell} = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_{t} = 1$ if $t \geq 2018$. $\Delta P_{i\ell t}$ is the average *target* rate change for insurer i in line ℓ in year t, which is the premium-weighted average across all rate filings in a given year for line ℓ. μ_{ℓ} and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer and by year. From columns (1) through (4), I progressively add controls and fixed effects. (Data Source: S&P Global)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Commercial × Post	8.083***	8.659***	8.681***	9.594**
	(1.527)	(1.483)	(1.645)	(2.937)
Product Line FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Insurer FE			Yes	
Insurer-Year FE				Yes
Controls		Yes	Yes	Yes
Time Period	2013-2021	2013-2021	2013-2021	2013-2021
R2	0.0362	0.0569	0.352	0.535
Observations	3405	2855	2855	2855

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A9: **Insurers' Price Response: Difference-in-Difference using Treatment Window**

This table reports the results from estimating Equation (13):

$$\Delta P_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t the year. The years 2015–2017 are are excluded. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. $\Delta P_{i\ell t}$ is the average rate change for insurer i in line ℓ in year t, which is the premium-weighted average across all rate filings in a given year for line ℓ. μ_ℓ and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer and by year. From columns (1) through (4), I progressively add controls and fixed effects. (Data Source: S&P Global)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Commercial × Post	6.210***	6.172***	5.966***	5.323**
	(1.392)	(1.267)	(1.279)	(1.511)
Product Line FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Insurer FE			Yes	
Insurer-Year FE				Yes
Controls		Yes	Yes	Yes
Time Period	2012-2020	2012-2020	2012-2020	2012-2020
R2	0.0928	0.114	0.316	0.527
Observations	2924	2531	2531	2531

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A10: **Insurers' Price Response: Difference-in-Difference using Continuous Treatment**

This table reports the results from estimating Equation (13):

$$\Delta P_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{DiscussionIntensity}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{DiscussionIntensity}_t$ is the share of unique earnings calls that discuss "social inflation" among top 25 insurance groups. $\Delta P_{i\ell t}$ is the average rate change for insurer i in line ℓ in year t, which is the premium-weighted average across all rate filings in a given year for line ℓ. μ_ℓ and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer and by year. From columns (1) through (4), I progressively add controls and fixed effects. (Data Source: S&P Global)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Commercial × Discussion Share	0.0738***	0.0723***	0.0739***	0.0769***
	(0.00951)	(0.00939)	(0.0111)	(0.0157)
Product Line FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Insurer FE			Yes	
Insurer-Year FE				Yes
Controls		Yes	Yes	Yes
Time Period	2013-2021	2013-2021	2013-2021	2013-2021
R2	0.0878	0.108	0.309	0.540
Observations	4397	3761	3761	3761

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A11: **Cross-State Heterogeneity in Social Inflation**

This table summarizes the heterogeneity across geography in the incidence of extreme verdicts and settlements against corporate defendants, focusing on the top 20 states with the highest number of counts from 2001 to 2021. For each seven-year time period, I report the number and the total sum of awards greater than $10 million. Units are in $ millions. (Data Source: VerdictSearch)

state	2001-2007	2008-2014	2015-2021	Total
Florida	412.0	458.8	2255.9	3126.8
Texas	291.4	414.9	2278.9	2985.1
California	601.6	1132.2	1052.8	2786.6
New York	231.8	298.5	407.7	938.1
Georgia	26.7	162.6	693.7	883.1
Illinois	283.0	118.1	201.4	602.5
Louisiana	91.3	146.0	61.3	298.6
New Mexico	0.0	58.5	233.0	291.5
Pennsylvania	62.7	99.3	120.2	282.2
Maryland	0.0	119.3	105.5	224.8
Missouri	152.5	65.2	0.0	217.7
Ohio	35.6	81.4	72.3	189.3
New Jersey	76.8	47.6	61.8	186.1
Connecticut	53.3	65.9	51.6	170.8
Virginia	72.0	88.3	0.0	160.3
Kentucky	27.0	0.0	106.1	133.2
Michigan	85.7	17.8	27.3	130.8
Indiana	71.0	15.2	32.5	118.7
South Carolina	12.0	0.0	86.1	98.1
Massachusetts	20.0	0.0	68.9	88.9

Table A12: **Cross-County Heterogeneity in Social Inflation**

This table summarizes the heterogeneity across geography in the incidence of extreme verdicts and settlements against corporate defendants, focusing on the top 20 counties with the highest number of counts from 2001 to 2021. For each seven-year time period, I report the number and the total sum of awards greater than $10 million. Units are in $ millions. (Data Source: VerdictSearch)

venue	2001-2007	2008-2014	2015-2021	Total
Nassau County	26.8	12.9	1046.4	1086.1
Los Angeles County	210.9	375.8	474.5	1061.3
Broward County	30.6	28.6	913.6	972.8
Titus County	0.0	0.0	756.0	756.0
Harris County	84.4	0.0	566.8	651.2
Cook County	180.1	61.1	201.4	442.6
Upshur County	0.0	10.5	388.8	399.3
Orange County	212.6	101.9	37.0	351.5
Dallas County	20.8	99.4	193.5	313.8
Muscogee County	0.0	0.0	307.1	307.1
Federal	111.5	108.1	85.7	305.2
Miami-Dade County	233.7	71.2	0.0	304.9
Santa Fe County	0.0	58.5	206.0	264.5
San Bernardino County	0.0	84.9	170.9	255.7
Prince George's County	0.0	109.3	105.5	214.8
Kings County	54.0	67.0	92.5	213.4
New York County	14.1	26.9	168.8	209.8
Union County	15.0	0.0	175.9	190.9
Bronx County	50.0	44.8	75.1	169.8
Hidalgo County	0.0	88.0	80.0	168.0

Table A13: **Insurers' Price Response: Large Insurers Only**

This table reports the results from estimating the difference-in-difference and the triple-difference specifications for insurer with net total assets greater than \$1 billion in a given year. The difference-in-difference specification is given as in Equation (13):

$$\Delta P_{i\ell t} = \alpha + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. $\Delta P_{i\ell t}$ is the average rate change for insurer i in line ℓ in year t, which is the premium-weighted average across all rate filings in a given year for line ℓ. μ_ℓ and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer and by year. The results are displayed in columns (1) through (3).

The triple-difference specification is given as in Equation (15)

$$\begin{aligned}\Delta P_{is\ell t} = {} & \alpha_0 + \alpha_1 (\text{Commercial}_\ell \times \text{Post2018}_t) + \alpha_2 (\text{Commercial}_\ell \times \text{HighExposure}_s) \\ & + \alpha_3 (\text{HighExposure}_s \times \text{Post2018}_t) + \beta \times (\text{Commercial}_\ell \times \text{HighExposure}_s \times \text{Post2018}_t) \\ & + \mu_s + \mu_\ell + \mu_{it} + \epsilon_{is\ell t}\end{aligned}$$

where i denotes the insurer, s denotes the state, ℓ denotes the product line, and t denotes the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. Furthermore, $\text{HighExposure}_s = 1$ if for state s, Exposure_s is above the median value across states, where Exposure_s is computed as the total verdicts greater than \$25 million in each state from 2001 to 2014, scaled by the total premiums sold in state s in 2014. $\Delta P_{is\ell t}$ is the average annual rate change, which is the premium-weighted average across all rate filings in a given year for line ℓ in state s. μ_s, μ_ℓ and μ_{it} represent state, product line and insurer-year fixed effects, respectively. Insurer-level controls include log(assets), leverage, asset growth, and return on equity, and state-level controls include GDP growth and change in the number of truck accidents. Standard errors are clustered by insurer and by state. The results are displayed in columns (4) and (5). (Data Source: S&P Global, FRED, NHTSA)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change	(5) Rate Change
Commercial × Post	5.066***	5.049***	5.365**	4.124***	4.000***
	(1.078)	(1.370)	(1.767)	(0.609)	(0.602)
Commercial × High Exposure × Post				2.227**	2.030**
				(0.698)	(0.746)
Controls	Yes	Yes	Yes	Yes	Yes
Product Line FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes		Yes	Yes
Insurer FE		Yes			Yes
Insurer-Year FE			Yes		
Sample	Baseline	Baseline	Baseline		
Time Period	2013-2021	2013-2021	2013-2021	2013-2021	2013-2021
R2	0.122	0.259	0.507	0.138	0.253
Observations	1676	1676	1676	13027	13027

Table A14: **Insurers' Reserve Response to Social Inflation: Difference-in-Difference**

This table reports the results from estimating Equation (13):

$$\phi_{i\ell t} = \alpha + \beta \times (\text{Commercial}_{\ell} \times \text{Post2018}_{t}) + \mu_{\ell} + \mu_{it} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ denotes the product line, and t the year. $\text{Commercial}_{\ell} = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_{t} = 1$ if $t \geq 2018$. $\phi_{i\ell t}$ is the average reserve per claim that insurer i allots to product line ℓ in year t, which is computed by dividing the aggregate amount of reserves in line ℓ divided by the total number of outstanding insurance claims. μ_{ℓ} and μ_{it} represent product line and insurer-year fixed effects, respectively. Standard errors are clustered by insurer and by year. From columns (1) through (3), I progressively add additional fixed effects. (Data Source: S&P Global)

	(1) Reserve per Claim	(2) Reserve per Claim	(3) Reserve per Claim
Treat × Post	18.21**	18.66**	16.38**
	(6.154)	(5.918)	(4.911)
Product Line FE	Yes	Yes	Yes
Year FE	Yes	Yes	
Insurer FE		Yes	
Insurer-Year FE			Yes
R2	0.332	0.700	0.862
Observations	9084	9077	9048

Table A15: **Realized Losses by Financial Constraints**

This table reports the results from estimating Equation (16):

$$\Delta L_{i\ell t} = \alpha + \delta \text{Constrained}_{it} + \beta \times (\text{Commercial}_\ell \times \text{Post2018}_t) + \gamma \times (\text{Commercial}_\ell \times \text{Post2018}_t \times \text{Constrained}_{it}) + \mu_\ell + \mu_{it} + \text{Controls} + \epsilon_{i\ell t}$$

where i denotes the insurer, ℓ the product line, and t the year. $\Delta L_{i\ell t}$ is the average annual change in losses, defined as $(L_{i\ell t} - L_{i\ell,t-1})/(0.5L_{i\ell t} + 0.5L_{i\ell,t-1})$. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. $\text{Constrained}_{it} = 1$ if insurer i's risk-based capital (RBC) ratio in year $t-1$ is below the cross-sectional median in year $t-1$. μ_ℓ and μ_{it} represent product line and insurer-year fixed effects, respectively. The lagged controls include log(assets), leverage, asset growth, and return on equity. Standard errors are clustered by insurer and by year. From columns (1) through (3), I progressively add fixed effects. (Data Source: S&P Global)

	(1) Change in Loss	(2) Change in Loss	(3) Change in Loss
Commercial × Post × Constrained	-0.285	-0.243	-0.0956
	(0.328)	(0.372)	(0.231)
Commercial × Post	0.656	0.645	0.634
	(0.565)	(0.620)	(0.514)
Product Line FE	Yes	Yes	Yes
Year FE	Yes	Yes	
Insurer FE		Yes	
Insurer-Year FE			Yes
Time Period	2013-2021	2013-2021	2013-2021
R2	0.00115	0.0585	0.500
Observations	9862	9862	9862

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A16: **A Model of Losses and Loss Reserves**

This table summarizes the estimated model of losses and loss reserves. For column (1), I report the estimates from the following regression:

$$V_{it} = b_0 + b_1 V_{i,t-1} + b_2 \left(V_{i,t-1} \times \text{Post2018}_t\right) + \epsilon_{it}$$

where V_{it} is the realized loss per policy for commercial auto liability for insurer i in year t and $\text{Post2018}_t = 1$ if $t \geq 2018$. In column (2), I report the estimates from the following regression:

$$\phi_{it} = c_0 + c_1 V_{i,t-1} + c_2 \left(V_{i,t-1} \times \text{Post2018}_t\right) + c_3\text{Post2018}_t + \epsilon_{it}$$

where ϕ_{it} is the loss reserve per policy for commercial auto liability for insurer i in year t. (Data Source: S&P Global)

	(1)	(2)
	Realized Loss(t)	Loss Reserve(t)
Loss(t-1)	0.784***	12.02***
	(0.0151)	(0.887)
Loss(t-1) × Post	0.0755***	2.831**
	(0.0139)	(1.103)
Post		9.247***
		(1.880)
Constant	0.327***	32.45***
	(0.0194)	(1.336)
Time Period	2013-2021	2013-2021
R2	0.594	0.200
Observations	4201	4009

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A17: **Top Insurers in Commercial and Personal Auto Liability**

This table summarizes the top 10 insurers in commercial auto and personal auto market by market share. The insurers that appear in the top 10 list for both lines are highlighted in **blue**. (Data Source: NAIC)

Ranking	Commercial Auto	Market Share (2018)	Personal Auto	Market Share (2018)
1	**Progressive**	10.88%	State Farm	17.05%
2	**Travelers**	6.34%	**Berkshire Hathaway**	13.44%
3	**Liberty Mutual**	4.44%	**Progressive**	11.00%
4	**Nationwide**	4.04%	**Allstate**	9.21%
5	**Berkshire Hathaway**	3.74%	USAA	5.88%
6	Old Republic	3.56%	**Liberty Mutual**	4.79%
7	Zurich	3.39%	Farmers	4.27%
8	Auto Owners	2.46%	**Nationwide**	2.73%
9	Tokio Marine	1.88%	**Travelers**	1.91%
10	Chubb	1.83%	American Family	1.91%

Table A18: **Insurers' Price Response: Triple-Difference using Alternate State Groups**

This table reports the results from estimating Equation (15):

$$\begin{aligned}\Delta P_{is\ell t} = &\ \alpha_0 + \alpha_1 \left(\text{Commercial}_\ell \times \text{Post2018}_t\right) + \alpha_2 \left(\text{Commercial}_\ell \times \text{HighHHI}_s\right) \\ &+ \alpha_3 \left(\text{HighHHI}_s \times \text{Post2018}_t\right) + \beta \times \left(\text{Commercial}_\ell \times \text{HighHHI}_s \times \text{Post2018}_t\right) \\ &+ \mu_s + \mu_\ell + \mu_{it} + \epsilon_{is\ell t}\end{aligned}$$

where i denotes the insurer, s denotes the state, ℓ denotes the product line, and t denotes the year. $\text{Commercial}_\ell = 1$ if product line ℓ is considered commercial auto liability, and $\text{Post2018}_t = 1$ if $t \geq 2018$. Furthermore, $\text{HighHHI}_s = 1$ if the state's HHI in commercial auto liability is above the median across states, and 0 otherwise. $\Delta P_{is\ell t}$ is the average annual rate change, which is the premium-weighted average across all rate filings in a given year for line ℓ in state s. μ_s, μ_ℓ and μ_{it} represent state, product line and insurer-year fixed effects, respectively. Insurer-level controls include log(assets), leverage, asset growth, and return on equity, and state-level controls include GDP growth and change in the number of truck accidents. Standard errors are clustered by insurer and by state. From columns (1) through (4), I progressively add controls and fixed effects. (Data Source: S&P Global, FRED, NHTSA)

	(1) Rate Change	(2) Rate Change	(3) Rate Change	(4) Rate Change
Commercial × Post	4.803***	4.864***	4.909***	4.468***
	(0.682)	(0.700)	(0.647)	(0.599)
Commercial × High HHI × Post	-0.681	-0.684	-0.806	-0.507
	(0.711)	(0.737)	(0.729)	(0.647)
Controls		Yes	Yes	Yes
Product Line FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Insurer FE			Yes	
Insurer-Year FE				Yes
Time Period	2013-2021	2013-2021	2013-2021	2013-2021
R2	0.111	0.118	0.244	0.440
Observations	23772	21152	21152	21152

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A19: **Insurer Exits**: **Robustness**

This table reports summary statistics on insurer exits. I report the number of insurers that exit a state in each year, where an exit of insurer i in state s at time t is defined as when the insurer i provides commercial auto liability coverage in state s at time $t-1$ but not at time t in the same state. To avoid spurious results, I require that the insurer was operating in years 2008–2010 and have at least 0.5% market share in any given state. Panel (a) provides summary by the size of insurers. The large insurers have more than 2% market share, and small insurers have less than 1% market share. The medium group encompasses the remaining insurers. Panel (b) provides summary by state groups. The low exposure states are the 17 states without any verdicts or settlements greater than $10 million in my sample. The high exposure states are the top 17 states, and the medium group encompasses the remaining states. (Data Source: S&P Global, VerdictSearch)

(a) Summary by Insurer Size

	All Sample	Large	Medium	Small
2011	308	43	94	171
2012	192	32	50	110
2013	166	24	51	91
2014	142	17	44	81
2015	126	26	39	61
2016	118	19	36	63
2017	125	19	26	80
2018	114	23	46	45
2019	101	18	33	50
2020	111	19	39	53
2021	105	14	33	58
2022	81	17	21	43

(b) Summary by State Group

	All Sample	High	Medium	Low
2011	308	121	95	92
2012	192	70	55	67
2013	166	74	44	48
2014	142	57	44	41
2015	126	51	31	44
2016	118	31	41	46
2017	125	49	39	37
2018	114	33	36	45
2019	101	36	29	36
2020	111	33	39	39
2021	105	38	29	38
2022	81	25	24	32