Insurers' M&A in the United States during the 1990–2022 period: Is the Fed monetary policy a causal factor?

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Abstract

We investigate the causes of the gap in mergers and acquisitions (M&As) between life and nonlife insurers in the US from 1990 to 2022. Our DID analysis indicates a parallel trend between M&As in the life insurance and nonlife insurance sectors from 1990 to 2012, and a significant difference after 2012. There was a shock in the life insurance market that resulted in a reduction in M&As after 2012. Variable annuity sales and profitability in the life insurance sector declined after 2012. We find evidence that low interest rates observed during the implementation of the Fed's quantitative easing policy from 2008 to 2012 caused the difference in M&As in the life sector after 2012.

Keywords: Merger and acquisition, life insurance, nonlife insurance, US insurance market, DID methodology, SDID model, quantitative easing monetary policy, life insurance annuity, variable annuity, risk management.

JEL codes: C21, D40, D80, G14, G22, G34.

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Introduction

Understanding the effect of monetary policy on financial institutions is very important because these institutions play a key role in the resource allocation and welfare of countries. The insurance sector is among the main risk managers in the US economy, and the consolidation of this sector is a central source of economic stability.

This paper is related to the literature on mergers and acquisitions (M&As) in the US insurance market. A significant decrease in M&As was observed after 2012 in the life insurance sector. We investigate the causes of the gap in M&As between life and nonlife insurers from 2013 to 2022. We first survey the M&A transactions observed in the US insurance market from 1990 to 2022 and select the M&A transactions linked to US target insurers. We analyze the behavior of the two groups of insurers (life and nonlife) over time to determine whether there are any parallel trends between the M&A evolution of target insurers in these two sectors from 1990 to 2012. We then empirically test the difference between M&As in the US life and nonlife insurance sectors after 2012, using the difference-in-differences (DID) methodology.

Our analysis does not reject a parallel trend between M&As in the life insurance and nonlife insurance sectors from 1990 to 2012 and confirms a significant difference after 2012. Our analysis shows that there was a shock in the life insurance market that resulted in the significant difference between M&As in the life and nonlife insurance sectors after 2012. The main reason for this decline in the life insurance sector is the decline of variable annuity sales and the corresponding reduction in profitability. We find evidence that the low interest rates observed after the implementation of the Fed's quantitative easing (QE) policy from 2008 to 2012 caused the difference by reducing M&As in the life insurance sector after 2012.

At the end of the 2007–2009 financial crisis, US monetary authorities made a major shift to their monetary policy. Specifically, they bought large-scale assets in order to inject liquidity into the economy through the QE policy. By implementing this policy, the Fed kept its key interest rate at a very low level, for long enough. The QE policy was implemented from 2008 to 2012, and low interest rates were maintained for many years after 2012. During the QE1 phase, the 10-year Treasury yield dropped 107 points. Other significant drops were observed in the QE2 and QE3 phases. In 2012, a plan to increase long-maturity Treasury security holdings to $45 billion per month was implemented. As a result, variable annuity products became less attractive to investors, leading to a decline in sales after 2012. In addition, many insurers increased their fees, and others stopped offering minimum return guarantees in response to falling interest rates because this risk management policy became very expensive. This accentuated the decline in sales after 2012. We analyze in detail how the monetary policy affected this decline in the life insurance market after 2012, following the low interest rates resulting from the implementation of the QE policy.

The rest of the paper is organized as follows. Section 1 reviews the main contributions in the literature on mergers and acquisitions in the insurance sector. We also cover analyses on the effects of monetary policy in the insurance sector. Section 2 analyzes the main characteristics of the US insurance market during the 1990–2022 period. Section 3 presents the evolution of M&A in the US insurance market from 1990 to 2022, while Section 4 is dedicated to a parallel trend analysis. We then present the DID analysis in Section 5, and the effects of the 2012 shock in the life insurance sector on M&As in Section 6. Section 7 concludes the paper. Additional information is available in Online appendix.

1. Literature review

1.1. Rationale for M&As

Usually, bidders initiate M&A transactions only when they anticipate that these activities will create value for their shareholders. Thus, studying the impact of such deals on bidders' performance is of particular interest, especially for intra-industry transactions, because these are most likely to be driven by synergies, and hence, create value. The empirical literature shows that acquiring insurers in the US insurance industry experience greater efficiency and higher profitability three years after the M&A (Cummins et al., 1999; Cummins and Xie, 2008; Boubakri et al. 2008).

Among insurers' economic rationales for these operations are a desire to increase their geographical reach and product range (Amel et al., 2004) and to benefit from economies of scale and scope (Cummins et al., 1999). Further, insurers may initiate these transactions to benefit from financial synergies (Chamberlain and Tennyson, 1998), to reduce their riskiness, and/or to improve the amount/timing of their cash flow streams (Cummins and Weiss, 2004). Estrella's (2001) findings refute the risk-reduction argument from transactions between different industries. Indeed, the article shows that the median probability of failure resulting from combinations of two property-casualty firms is lower than from a combination of a property-casualty firm and a bank holding company.

Akhigbe and Madura (2001) report a positive and significant abnormal return for acquiring insurers and conclude that this favorable valuation effect is driven by the similarity of services provided by both the acquirer and the acquired. In other words, standardization in their products makes the merger of operations easier for both parties. Akhigbe and Madura (2001) document a higher positive and significant market effect for acquirers that are nonlife insurers. Floreani and Rigamonti (2001) also report a positive and significant valuation effect for the bidder, following M&A transactions involving pure insurance partners. This market valuation is positive but slightly lower when the target firm is publicly traded. Only transactions involving insurers buying insurers seem to create value for the bidder. Indeed, Cummins and Weiss (2004) report a small negative valuation effect on the bidder's shares following transactions that do not involve pure insurance partners.

The financial literature also suggests that M&A transactions may destroy rather than create value, especially if these transactions are motivated by managerial hubris, that is, where managers are more interested in maximizing the size of their business empires than in returning cash to shareholders (Roll, 1986; Denis and McConnell, 2003; Boubakri et al., 2008). Hence, a negative impact on the bidder's firm value could be observed. Results relating to CEO characteristics indicate that the percentage of shares held by the CEO and the CEO duality (CEO and board chair) are significantly and negatively related to the bidder's long run performance, which is consistent with managerial entrenchment theory related to CEO ownership. For such behavior to be constrained, effective governance mechanisms must be put in place, such as 1) a strong board with competent independent directors, and 2) a legal environment that offers strong protection to minority shareholders. The legal environment relates not only to investor protection but also to transparency and overall quality of accounting standards, which were all recently shown, by Rossi and Volpin (2004) and Moeller and Schlingemann (2005), to be significant determinants of M&As. Asymmetric information between acquiring firms on particular targets can also affect M&A activities by modifying the premiums of different deals (Betton et al., 2009; Brockman and Yan, 2009; Dionne et al., 2015).

Additionally, cross-border transactions may generate a higher positive valuation effect for the bidder because they are perceived to lead to a geographic expansion of their market. The results of Floreani and Rigamonti (2001) support this argument. Specifically, they demonstrate that transactions involving insurance partners that are both located in European Union countries are not welcomed by the financial market. On the other hand, cross-border transactions may also destroy value for the bidder because they are more difficult to manage (Cummins and Weiss, 2004)—a result not supported by Floreani and Rigamonti (2001). In Appendix A, we present a detailed analysis of various contributions on mergers and acquisitions in the insurance industry by focusing on their methodology. Very few contributions used causality analysis.

1.2. Monetary policy and insurance

Pellizon and Sottocornola (2018) studied the effect of QE monetary policies on insurance markets with an emphasis on European insurers. They indicate that extremely low interest rates constitute a major source of risk for life insurers and, particularly, for those offering financial products with guaranteed rates of return. Their event study shows, however, a moderate negative effect of the European QE policy on the insurance industry.

Other researchers verified that German insurers had difficulty meeting the Solvency II capital requirements following the QE policy (Deutsche Bundesbank, 2013; Berdin and Gründl, 2015).[1]

Koijen and Yogo (2021) analyzed the effect of minimum return guaranties on life insurers. Variable annuity insurers offering put options to guarantee minimum returns to their clients become risk managers that are exposed to low interest risk. The authors discuss potential regulatory changes to ensure more stability in the life insurance sector. On variable annuity risks, see also Chahboun and Hoover (2019), Egan et al. (2021), Gagnon et al. (2011), Verani and Yu (2021), and Gatzert and Schmeiser (2024). None of these studies have related low interest rates to mergers and acquisitions in the insurance industry.

2. The US insurance market

The insurance industry comprises three main sectors. The first is property and casualty insurance (P&C). It covers property damage and miscellaneous risks (coverage for the insured's movable and immovable property) and civil liability (coverage for damage of all kinds caused by the insured to third parties). The second sector is health insurance. It covers medical services received from different providers. The third sector is life insurance (life insurance coverage and life annuity contracts). This insurance sector collects a higher volume of premiums than the other two. In our analysis, target insurers with SIC code 6331 are insurers in the P&C market.[2] Target insurers with SIC codes 6321 and 6324 are insurers

[1] See also Holsboer (2000) and Wedow and Kablau (2011) on the effect of low interest rates on German insurers.

[2] Surety Insurance (6351), Title Insurance (6361), and Insurance Carriers Not Elsewhere Classified (6399) are included in the P&C sector.

corresponding to the health insurance market (Accident and Health Insurance, and Hospital and Medical Service Plans). Target insurers with SIC code 6311 are from the life insurance market (Life). Table 1 summarizes the division of insurance sectors.

We first group the three insurance sectors into two major groups, according to the way in which insurance is managed and the duration of the contract: 1) life insurance, made up of the life insurance sector (Life); and 2) nonlife insurance (Nonlife), made up of the property and casualty insurance sector and the health insurance sector. This classification is often used by the OECD to distinguish between the life and nonlife insurance sectors. This separation simplifies the DID application, although it is not necessary, as we will see in the robustness analysis, where we consider the three groups separately with two control groups and one treatment group.

Table 1: Summary of the different insurance categories in our two groups

Nonlife insurance			Life insurance
Property damage and miscellaneous risks	Civil liability	Health insurance	Life insurance and annuities
Coverage for movable and immovable property belonging to the insured	Coverage for damage of any kind caused by the insured to third parties	Coverage for medical services to the insured	Guarantees in the event of the insured's life or death; annuities
Insurers with SIC codes 6321, 6324, 6331, 6351, 6361, and 6399.			Insurers with SIC code 6311

3. M&A transactions related to US target insurers from 1990 to 2022

From the SDC database, we identify 3,366 M&A transactions related to US target insurers from 1990 to 2022. Data are annual observations as of December 31 of each year. Figure 1 identifies the two main waves of target insurer M&As recorded in the US insurance industry over the past 33 years. There was strong M&A growth until the years 1997 to 1999, when the market reached its first peak since 1990.

After a sharp decline in 2000, the M&A market resumed growth in 2003, and reached its second peak in 2007. Each of these wave years has more than 120 annual transactions. The two peaks correspond to periods of economic expansion. The wave recorded around 1997–1999 represents the largest for the US insurance industry during the period of analysis. The record years of 1998 and 1999 have not been broken since. In fact, this period corresponds to the Internet and new technology growth of 1998–2000. The years of the second largest wave of M&As correspond to the economic expansion period before the financial crisis that began in August 2007. The post-2012 period is less active, with a partial recovery in 2021 and 2022.

Figure 2 depicts three peaks of M&As across all industries in the US (1998, 2007, and 2017) during the same period. As documented above, only two waves of M&As occurred in the US insurance industry during that period. Since the 2007 peak, the M&A market has exhibited an overall downward trend throughout the US insurance industry (life and nonlife combined). By comparison, the all-industry M&A market resumed its overall upward trend after a short decline during the financial crisis, from 2007 to 2009, and reached a new peak in 2017. Figure 2 suggests that the post-2012 period is marked by a behavioral shift among insurers across the US insurance industry.

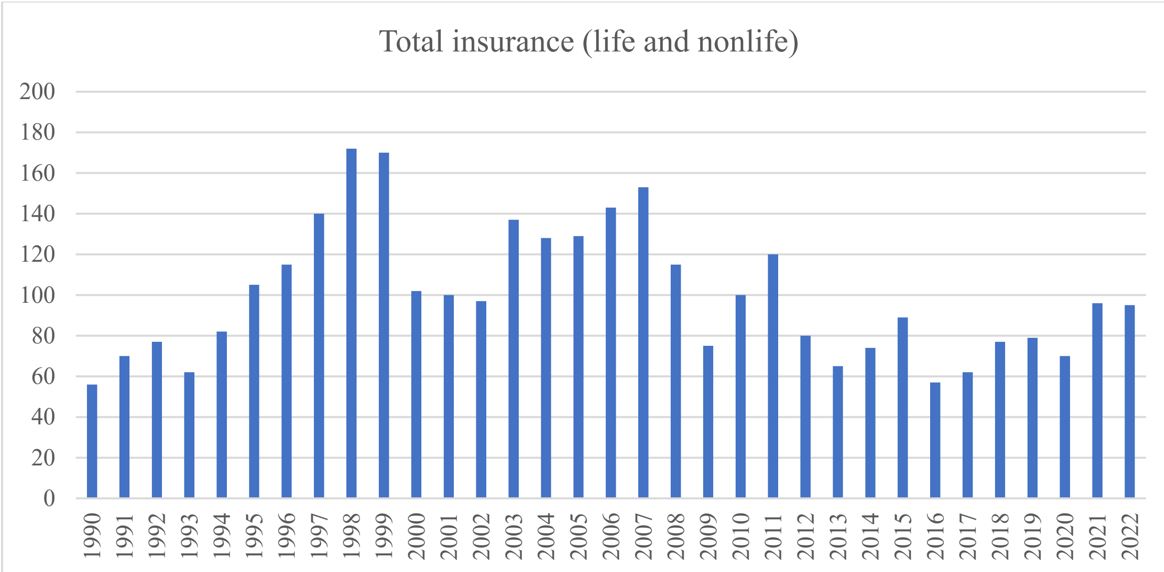

Figure 1: Histogram of the annual number of M&A transactions related to US target insurers, 1990–2022

Data source: SDC database.

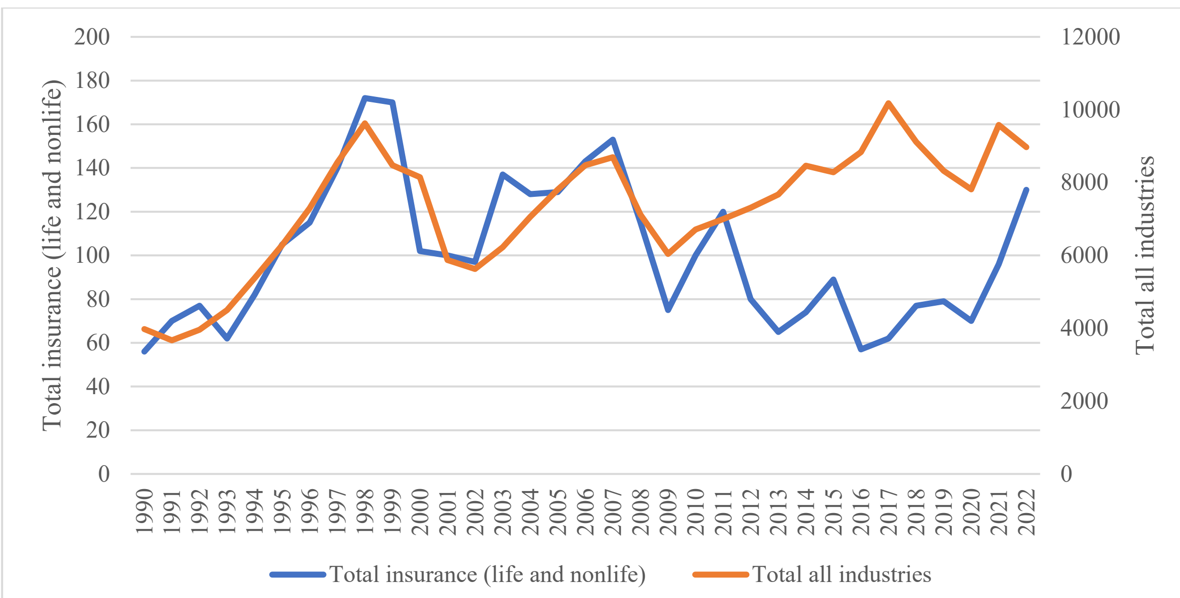

Figure 2: M&A trends in the US insurance industry (total M&A for nonlife and life targets, left) and for all industries in the US (right), 1990–2022

Data source: SDC database.

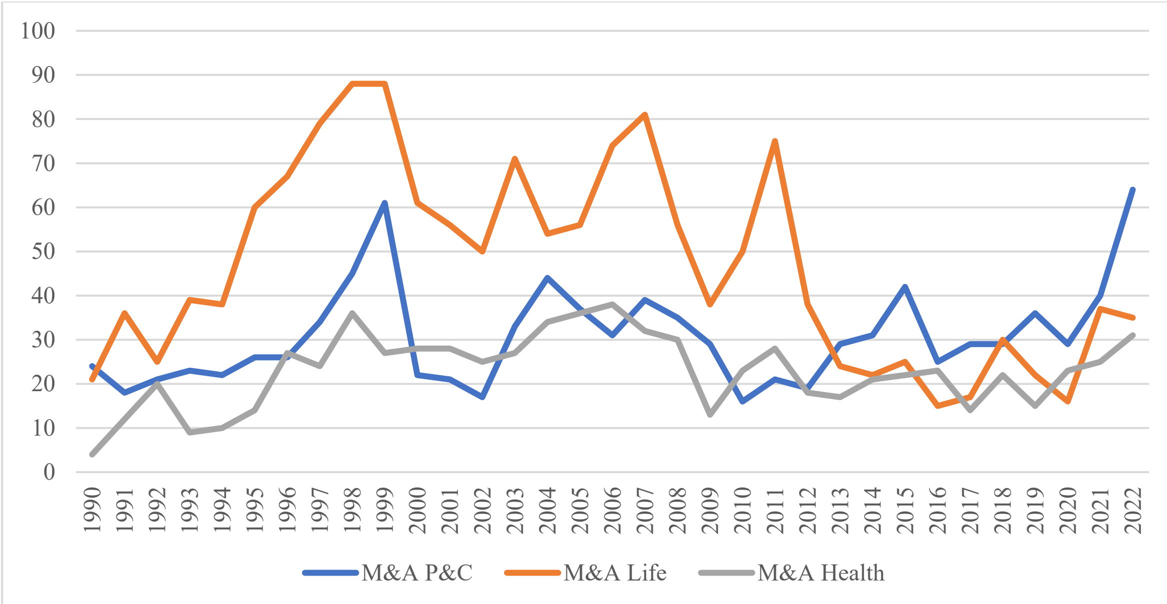

Figure 3: M&A trends of target insurers by the three insurance sectors
in the US, 1990–2022

Data source: SDC database.

Table 2: Annual mean and standard deviation of the M&A in each sector

	1990–2022		1990–2012		2013–2022	
Period	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
P&C sector	30.848	11.353	28.870	10.981	35.400	11.423
Life sector	46.788	22.342	56.565	19.294	24.300	7.660
Health sector	22.909	8.402	23.609	9.524	21.300	5.012

Data source: SDC database.

Figure 3 presents the evolution of the annual numbers of M&As in the three insurance lines, and Table 2 summarizes their main statistics. Property and casualty insurers and health insurers appear to be more similar to each other than to life insurers. We also observe a large reduction in M&As in the life sector after 2012.

As already mentioned, we consider that the US insurance industry consists of two main lines of business: life insurance and nonlife insurance, the latter including P&C insurance and health insurance. Given that the two main lines of insurance can be affected differently by market conditions and climate risk, we have plotted the M&A transactions recorded in each of these two lines in order to analyze their behavior in relation to the target insurer M&A activity. Figure 4 shows the evolution of M&As in each of the two main US insurance lines over the period of 1990 to 2022. We confirm the strong decrease in M&As in the life insurance industry after 2012, while this activity seems more stable in the nonlife insurance sector during the same period.

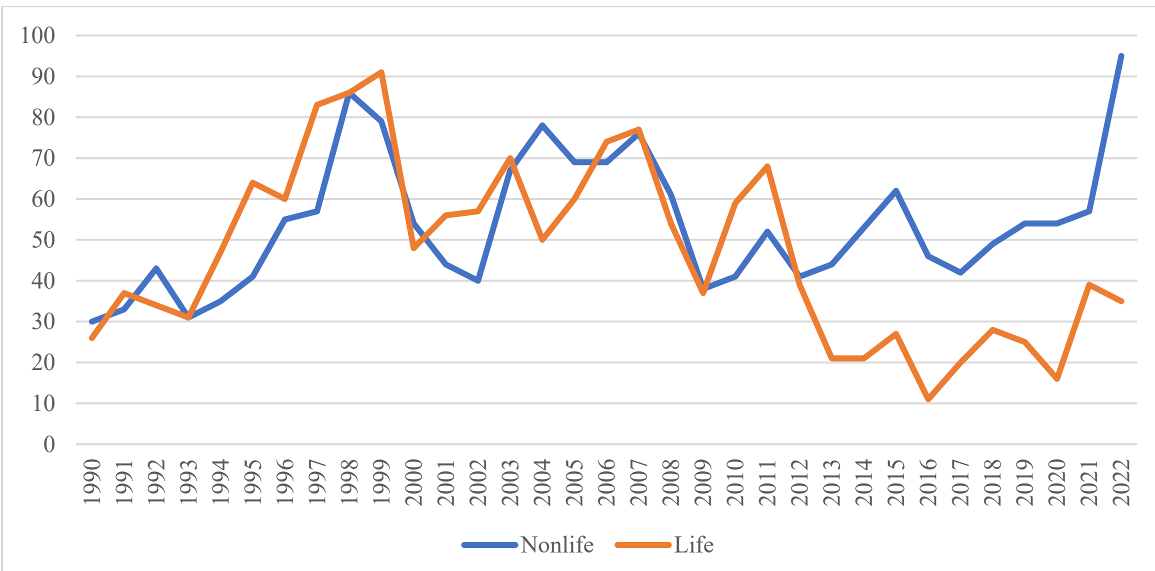

Figure 4: M&A trends of target insurers by the two main insurance sectors (life and nonlife) in the US, 1990–2022

Data source: SDC database.

Figure 4 also shows a parallel time trend in the evolution of target insurer M&As for life and nonlife insurance from 1990 until 2009 and even 2012 (see the corresponding Table B1 in Appendix B). This result suggests that the evolution of target insurer M&As in the nonlife insurance sector is almost identical to that observed in the life insurance sector during this period. The parallel trends observed between the two groups started to disappear after 2009. The difference is more pronounced after 2012. Based on Figure 4, we select the years 2009 and 2012 as potential candidates for a treatment date in our analysis with the DID method. The choice of the treatment date for our DID method thus seems ambiguous. We now use statistical tests to validate the year that best suits our data.

4. Validation of the selected treatment date and the presence of parallel trends

Based on Figure 4, we have identified two years in which the parallel trends observed between our two groups began to disappear: 2009 and 2012. We define our treatment effect as a difference between the average number of M&As per year of target insurers in the life insurance sector and the average number of M&As of target insurers in the nonlife insurance sector.

4.1. Validation of the choice of treatment date using five statistical tests

To choose the most appropriate treatment date for our data, we use a statistical approach applied to the annual M&A data in the two insurance sectors (Imbens and Wooldridge, 2009; Roberts and Whited, 2012; Dionne, 2024). We first calculate the annual difference between the number of M&As of target insurers in the life insurance sector versus the number of M&As of target insurers in the nonlife insurance sector, as observed over our entire study period, that is 1990 to 2022. Next, we calculate the mean and median of the difference between the number of target insurer M&As in the life insurance sector and the number of target insurer M&As in the nonlife insurance sector over the pre-treatment period (including the year of the candidate date) and over the post-treatment period, for each of our two selected candidate dates (2009 and 2012). Finally, we perform five statistical tests—the mean statistical test (Student), the median statistical test, the Wilcoxon test, the monotonicity hypothesis, and the median-criteria test—to validate the choice of treatment date.

4.1.1. Three basic tests

The results of the first three tests are presented in Table C1 (Appendix C), where the differences between various statistics are presented. Our first decision criterion for the choice of treatment date is to test the null hypothesis (H0) that the average number of M&As in the nonlife sector and the average number of M&As in the life sector are statistically similar (Student's test) over the period from 1990 to the end of the candidate date (2009 or 2012) on the one hand, and, on the other hand, to test the null hypothesis (H0) that the average number of M&As in the nonlife sector and the average number of M&As in the life sector are statistically different over the post–treatment date period (post-2009 or post-2012) due to the treatment effect. We also test the null hypotheses for the median and with the Wilcoxon (or distribution) test. According to the analysis presented in Appendix C, the three tests cannot discriminate between the two periods (1990–2009 vs. 1990–2012).

4.1.2. Monotonicity hypothesis

We employ an additional criterion, the monotonicity hypothesis, to evaluate the treatment effect. This hypothesis postulates that when there is a change, the treatment effect can only go in one direction. To choose our treatment date based on the criterion of the monotonicity assumption, we used a graphical approach based on the analysis of Figure 5.

Figure 5 clearly shows a large difference between the number of M&As of target insurers in the nonlife insurance sector compared to the number of M&As of target insurers in the life insurance sector observed over the post-2012 period. Moreover, we note that our treatment effect, defined as a difference between the number of M&As per year of target insurers in the life insurance sector and the number of M&As of target insurers in the nonlife insurance sector, is negative for each year of the post-2012 period (10 years with a negative difference versus 0 years with a positive difference). In other words, 2012 changes the treatment effect in only one direction (negative difference) for each of the years in the post-2012 period. This affirms the monotonicity hypothesis. By contrast, Figure 5 shows that the year 2009 does not cause a change in the treatment effect in a single direction for each of the years in the post-2009 period (11 years with a negative difference versus 2 years with a positive difference). This violates the monotonicity hypothesis. In conclusion, because only the year 2012 meets the monotonicity condition, we select the year 2012 as the treatment date for our DID method with this hypothesis.

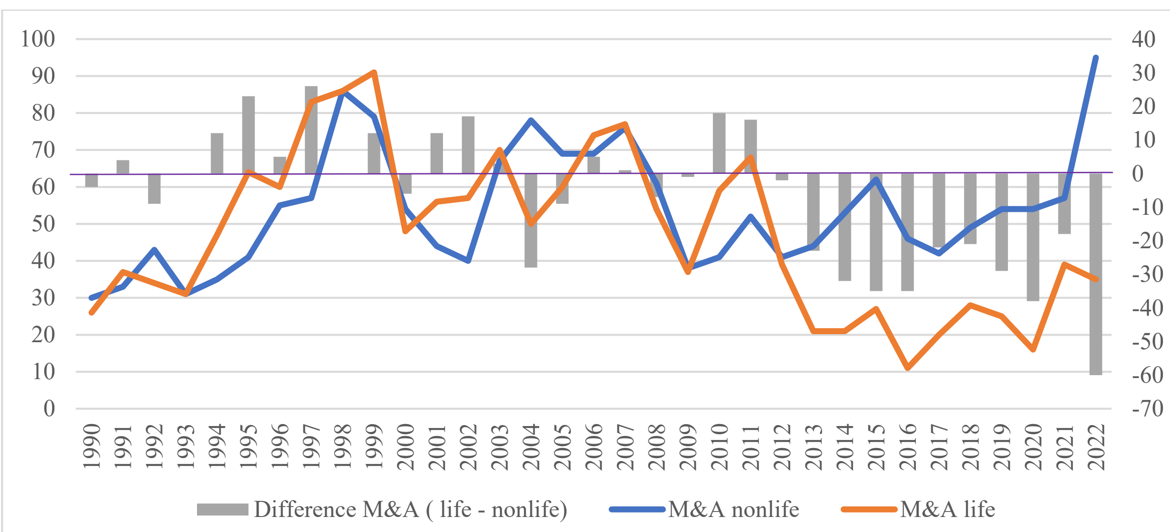

Figure 5: Evolution of the number of M&As per year in each of the two insurance sectors (nonlife and life, left) and their difference (in histogram, right)

Data source: SDC database.

4.1.3. Median-criteria test

For robustness, a last statistical criterion based on the median is applied to ensure the reliability of the choice of the selected year 2012. To do this, we draw on the work of Guest (2021), who applies a median-based statistical criterion. This allows us to define a selection criterion whereby the treatment effect for each of the years in the post-treatment period (post-2009 or post-2012) is lower than the median value of the difference between the number of M&As per year of target insurers in the life insurance sector and the number of M&As of target insurers in the nonlife insurance sector over our entire study period (1990 to 2022), which is equal to -2 (see Table C1). This criterion also supports the choice of 2012 as the treatment date for our DID method. As can be seen in Figure 5, the negative difference between the number of M&As per year of target insurers in the life insurance sector and the number of M&As of target insurers in the nonlife insurance sector is lower than the median value of our entire study period (1990 to 2022) for each of the years in the post-2012 period. This is not the case for the post-2009 period, where we in fact observe a positive difference for the years 2010 and 2011, which is thus higher than the median of the entire sample.[3] Therefore, our median-based criterion rejects the choice of the year 2009 as the treatment date for our DID method.

4.2. Parallel trends analysis

We now perform a validation test for the presence of parallel trends before 2013. To do this, we first create 33 dummy variables for each of the years in the period of 1990 to 2022. Then, we define a dummy variable Treated_L equal to 1 for the treated group. We also

[3] The negative value for 2012 is -2, as documented in Table B1.

create 33 interaction variables between the Treated dummy and the year dummy for each year from 1990 to 2022. Finally, we regress our dependent variable, number of M&s per year and state in the two insurance sectors, on our 33 Treated_L×Year interaction variables in each of the 51 states and using the OLS method of estimation for panel data. With the OLS method, we capture the individual effect (state) and the time effect (year). The results are presented in Table 3, with 3,366 observations (33×51×2) for the main test.

The results of our regressions validate the presence of a parallel trend before the end of 2012. As can be observed, the obtained coefficients are overall not statistically significant for the pre-treatment period. Our F-test supports this result. It shows that the F-statistic on our Treated_L×Year interaction variables prior to and at the treatment date (1990 to 2012) is $F(23, 2250) = 1.10$ with a probability $Prob > F = 0.3338$.We do not reject the null hypothesis at 5%. By contrast, the coefficients obtained for each of the years during the post-2012 period are all statistically significant at the 1% level (except for the year 2021, at 10%). Our F-test supports this result: $F(9, 1009) = 5.87$ with $Prob > F = 0.0000$. We reject the null hypothesis at 5% and can thus say that the coefficients considered as a whole are significant over the post-2012 period. These results validate our parallel trend test econometrically and thus confirm the choice of the year 2012 as the treatment year to be selected for our DID method.

Table 3: Parallel trends analysis for DID validation test of M&A in each state, each year, and each sector

	Parallel trends		Validation tests			
Independent variable	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Treated_L×Year1990	-0.078	0.11	–		–	
Treated_L×Year1991	0.078	0.197	0.078	0.129	–	
Treated_L×Year1992	-0.176	0.136	-0.176	0.128	-0.176	0.123

Independent variable	Parallel trends Coefficient	Standard error	Validation tests Coefficient	Standard error	Coefficient	Standard error
$Treated_L$×Year1993	0	0.156	0	0.156	0	0.155
$Treated_L$×Year1994	0.235	0.147	0.235	0.152	0.235	0.168
$Treated_L$×Year1995	0.451***	0.154	0.451***	0.15	0.451***	0.139
$Treated_L$×Year1996	0.098	0.23	0.098	0.259	0.098	0.21
$Treated_L$×Year1997	0.510***	0.16	0.510***	0.162	0.510***	0.161
$Treated_L$×Year1998	0	0.234	0	0.256	0	0.28
$Treated_L$×Year1999	0.235	0.172	0.235	0.17	0.235	0.179
$Treated_L$×Year2000	-0.118	0.135	-0.118	0.144	-0.118	0.143
$Treated_L$×Year2001	0.235	0.17	0.235	0.162	0.235	0.17
$Treated_L$×Year2002	0.333*	0.183	0.333*	0.19	0.333*	0.186
$Treated_L$×Year2003	0.059	0.214	0.059	0.215	0.059	0.223
$Treated_L$×Year2004	-0.549***	0.194	-0.549***	0.191	-0.549***	0.196
$Treated_L$×Year2005	-0.176	0.154	-0.176	0.158	-0.176	0.148
$Treated_L$×Year2006	0.098	0.163	0.098	0.165	0.098	0.167
$Treated_L$×Year2007	0.020	0.176	0.020	0.202	0.020	0.198
$Treated_L$×Year2008	-0.137	0.212	-0.137	0.193	-0.137	0.173
$Treated_L$×Year2009	-0.020	0.129	-0.020	0.166	-0.020	0.117
$Treated_L$×Year2010	0.353**	0.135	0.353**	0.137	0.353**	0.135
$Treated_L$×Year2011	0.314*	0.164	0.314*	0.163	0.314*	0.161
$Treated_L$×Year2012	-0.039	0.19	-0.039	0.169	-0.039	0.177
$Treated_L$×Year2013	-0.451***	0.134	-0.451***	0.146	-0.451***	0.133
$Treated_L$×Year2014	-0.627***	0.137	-0.627***	0.139	-0.627***	0.138
$Treated_L$×Year2015	-0.686***	0.137	-0.686***	0.132	-0.686***	0.143
$Treated_L$×Year2016	-0.686***	0.154	-0.686***	0.158	-0.686***	0.144
$Treated_L$×Year2017	-0.431***	0.111	-0.431***	0.111	-0.431***	0.114
$Treated_L$×Year2018	-0.412**	0.163	-0.412**	0.171	-0.412**	0.161
$Treated_L$×Year2019	-0.569***	0.119	-0.569***	0.116	-0.569***	0.124
$Treated_L$×Year2020	-0.745***	0.163	-0.745***	0.164	-0.745***	0.165
$Treated_L$×Year2021	-0.353*	0.191	-0.353	0.226	-0.353*	0.202
$Treated_L$×Year2022	-1.176***	0.231	-1.176***	0.219	-1.176***	0.22
Constant	0.588***	0.048	0.647***	0.052	0.843***	0.043
State fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y
Double SE clustering	State/Year	State/Year	State/Year	State/Year	State/Year	State/Year
Observations	3,366		3,264		3,162	
R-squared	0.541		0.542		0.543	

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. We do not reject the parallel trends hypothesis during the 1990-2012 period.
Data source: SDC database.

To ensure the reliability of our validation test on the choice of treatment date for our DID method, we conduct two robustness tests. The first consists in ignoring the first year of observation, $Treated_L$×Year1990. The second test consists in ignoring the first two years of observations, $Treated_L$×Year1990 and $Treated_L$×Year1991. The results of these two robustness tests, presented in Table 3, confirm the validation of the year 2012 as the treatment date to be selected for our DID method.

5. DID analysis

5.1. Variable descriptions

5.1.1. Introduction

To isolate a causal effect related to the separation of life and nonlife insurers' M&As observed after 2012, we have opted for a natural experiment method using the standard DID method. This method is based on two groups: insurers who have received treatment (treatment group) and insurers who have not received treatment (control group). We will also consider three groups in the robustness analysis and two more flexible DID approaches.

5.1.2. Variables

Given that the purpose of our study is to explain the relative decline in M&As in the US life insurance sector, we have chosen life insurers as our treatment group. We determined the dichotomous variable $Treated_L$ as equal to 1 for the treatment group (life insurance sector) and 0 for the control group (nonlife insurance sector).

We have created an interaction variable between our two variables of interest, $Treated_L$ and Post2012, in order to assess the impact of the treatment on the units in our treatment group. Our interaction variable, $Treated_L \times Post2012$, enables us to capture the effect of the treatment administered to the units in the treatment group.

Table 4 provides a detailed description of the explanatory variables introduced into our model (1), together with their construction method. The goal is to use the DID method to empirically verify the difference between M&As in the life and nonlife insurance sectors in the US.

Table 4: Description of explanatory variables

Explanatory variable	Construction method
$\mathrm{Treated_L}$ (dichotomous)	$\mathrm{Treated_L}$ variable equal to 1 for the treatment group (life insurance sector) and 0 for the control group (nonlife insurance sector).
$\mathrm{Post2012}$ (dichotomous)	$\mathrm{Post2012}$ variable (including the treatment date) that takes the value 0 if the period is before the treatment and the value 1 if the period is after the treatment.
$\mathrm{Treated_L} \times \mathrm{Post2012}$ (dichotomous)	$\mathrm{Treated_L} \times \mathrm{Post2012}$ interaction variable that captures the effect of the treatment administered to units in the treated group (the life insurance sector) after the treatment.

We posit that the shock that occurred in 2012 weakened the insurance business performance of target insurers in the life insurance sector in the post-2012 period. This weakening has resulted in a decline in the number of M&As per year among targets in the life insurance sector relative to the nonlife insurance sector in the post-2012 period. We expect a negative sign for the coefficient of the variable $Treated_L \times Post2012$ on the number of M&A targets per state and per year.

Based on our variables of interest, we consider the following regression model:

$$\text{Nbr M\&A}_{it} = \alpha_0 + \alpha_1 \text{Treated}_L \times \text{Post2012} + c_i + \eta_t + \epsilon_{it} \quad (1)$$

where:

Nbr $\text{M\&A}_{it}$: number of M&As in state *i* at date *t* in each sector;

$\text{Treated}_L \times \text{Post2012}$ =1 for the treatment group after the treatment period; = 0 otherwise;

c_i: individual effect for state i;

η_t: temporal effect in period *t*;

ϵ_{it}: random effect in a given state i on a given date *t*.

5.2. Results

The results presented in the first column of Table 5 (basic model) indicate that the coefficient of our variable $\text{Treated}_L \times \text{Post2012}$ is negative and statistically significant at 1%. This suggests a causal downward effect on the number of M&As in the treated group in the post-2012 period.

We consider climate risk events as possible covariates that may affect the DID results. Table 5 also shows that climate risk events have no effect on the DID analysis. The event information is from the Verisk database, which documents all climate risk events of $25M or more of total insured property losses. The number of events is the total number per year, and state and insured losses are the total losses of the insurance industry per year and state (Dionne et al., 2023). Details on data used for this analysis are presented in Appendix E1.

Table 5: Results of the regression of model (1) using the OLS method
with fixed effects on the individual (state) and time (year)

Dependent variable:	Number of M&As per year and state (life and nonlife)		
Independent variable	Basic model	With number of events	With insured losses
$Treated_L$×Post2012	-0.689*** (0.127)	-0.689*** (0.127)	-0.689*** (0.126)
Number of events		0.002 (0.011)	
Insured losses			-1.27e-11 (3.16e-11)
Constant	1.093*** (0.015)	1.086*** (0.041)	1.099*** (0.021)
State fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
Double SE clustering	State/Year	State/Year	State/Year
Observations	3,366	3,366	3,366
R-squared	0.554	0.554	0.554

*** p<0.01. Standard errors were computed with the bootstrapping method clustered at the state level. The coefficients of TreatedL×Post2012 measure the treatment effect in the three specifications. The covariates Number of events and Insured losses, representing climate risk events and corresponding insured losses, are not statistically significant.
Data source: SDC database.

Table 6 presents an additional test for considering climate risk events (Kranz, 2022). The test takes into account time-varying covariates. Note that the first regression in Panel A omits observations with a treatment status equal to zero. The regression in Panel B uses the results of the Panel A estimation to define the dependent variable. The estimated effect of a given climate risk variable on the number of M&A per state and year, obtained in Panel A, is subtracted from the original dependent variables in the two sectors to create a new dependent variable in Panel B. We observe in Panel B that the results remain stable when compared to those of Table 5, even if the number of events is statistically significant to explain mergers and acquisitions when the treatment status is equal to zero.

Table 6: Additional test of the effect of climate risk on DID analysis for the 1990–2022 period

Panel A: Regression of the effect of climate risk variables on the number of M&As per year for observations with a treatment status equal to zero

Dependent variable:	Number of M&As per year and per state		
Independent variable	Coefficient	Coefficient	Coefficient
Events	0.0304** (0.014)		
Losses (in $ billion)		0.0000 (0.000)	
Log (1+losses)			0.0211 (0.022)
Constant	Y	Y	Y
Observations	1,683	1,683	1,683
R-squared	0.081	0.083	0.079

Panel B: Estimation of the average treatment parameter using the DID model for the 1990–2022 period

Dependent variable:	Number of M&As per year and per state in the two sectors		
Independent variable	Climate events	Insured climate losses	Log of climates insured losses
$Treated_L \times Post2012$	-0.689*** (0.134)	-0.689*** (0.134)	-0.689*** (0.131)
Constant	0.4728*** (0.028)	0.5472*** (0.028)	0.4959*** (0.028)
Observations	3,366	3,366	3,366
R-squared	0.5387	0.5447	0.5458

*** p<0.01, ** p<0.05. Each regression includes fixed effects for state and time. Standard errors were computed with the bootstrapping method clustered at the state level. Results in Panel B support the robustness of those obtained in Table 5 with a different method of introducing covariates in the basic model.
Data source: SDC database.

5.3. Robustness analysis[4]

We now investigate whether our conclusions are robust to alternative econometric causal methodologies. The standard DID relies on the parallel trends assumption, suggesting that, in the absence of the treatment, both groups would have experienced the same outcome trends. However, recent studies have revealed that the standard parallel trends methodology may be a questionable modelling assumption and that pre-trend tests may come with caveats (see, for example, Kahn-Lang and Lang, 2020). We thus use recent and more flexible econometric approaches that are less reliant on the parallel trends assumption, namely, the synthetic difference-in-differences (SDID) and the synthetic control (SC) methods of estimation.

The SC method was introduced in a series of seminal articles by Abadie and coauthors (Abadie, 2003; Abadie et al., 2010 and 2015; Abadie and L'Hour, 2021). This method aims to generate a single synthetic control group using a weighting of the potential control units, in such a way that this synthetic control is as closely matched as possible to the treated units in pre-treatment outcomes. Unlike the standard DID framework, where control units are equally weighted, the SC approach reweights control units and relaxes the need for the parallel trends assumption. These generated weights for control units are fixed over time and could be zero for some control units and large for others.

The second alternative econometric approach is the SDID, recently introduced in the literature by Arkhangelsky et al. (2021). SDID is a very flexible methodology that can be applied in panel datasets and that aims to link the standard DID and the SC methods to

[4] A more detailed analysis of this section is presented in Appendix D.

combine their attractive features. Like the standard DID, SDID allows a different trending for treated and control units prior to the event of interest, and like the SC method, the SDID reweights control units to generate an optimal matched control unit, which helps relax the parallel trends assumption.

Besides the weighting scheme for control units, the SDID, like the SC method, assigns different weights for pre-periods. Control units' weights ensure that the average outcome for the treated units is approximately parallel to the weighted average for control units during the pre-periods. Time weights are such that the average post-treatment outcome for each of the control units differs by a constant from the weighted average of the pre-treatment outcomes for the same control units.

Table 7 reports the results for the two additional methods where we no longer aggregate in Panel B the M&As in the health and the P&C sectors. Instead, we consider them as two different control groups. For comparison, we also present in the table the standard DID results with the two control groups having constant equal weights over time. These robustness tests show that the standard DID estimation of Table 5 remains in the range of the different coefficients we find with more flexible econometric methodologies. We also observe in Panel B that the SDID and the DID estimations for the treatment effect are more stable than the estimation by the SC method when comparing results in both panels. It seems that the SC method performs less well with long-range historical data. Additional results with covariates are presented in Appendix D.

Table 7: Estimation of the average treatment effect
using the DID, SDID, and SC models for the 1990–2022 period

Dependent variable:	Number of M&As per year and state		
Independent variable	DID	SDID	SC
Panel A: One control group			
$\text{Treated}_{L}\times\text{Post2012}$	-0.689***	-0.689***	-0.712***
	(0.117)	(0.108)	(0.150)
Observations (State-Year)	3,366	3,366	3,366
Panel B: Two control groups			
$\text{Treated}_{L}\times\text{Post2012}$	-0.680***	-0.651***	-0.614***
	(0.112)	(0.135)	(0.166)
Observations (State-Year)	5,049	5,049	5,049

*** p<0.01. Each regression includes a constant effect and a fixed effect for state and time. Standard errors were computed from the bootstrapping method clustered at the state level. The results in Panel B support the robustness of those obtained in Table 5 with two more flexible causality models, the SDID and the SC. Data source: SDC database.

6. Origin of the 2012 shock in the life insurance market

6.1. Interest rate policy and annuity sales in the post-2012 period

Following the financial crisis of 2007–2008, the US monetary authorities made a major shift in their monetary policy. This involved the purchase of large-scale assets in order to inject liquidity into the economy through QE policies. Specifically, the Fed applied three major quantitative easing measures. First, between early 2008 and March 2010, it purchased $1,750 billion in long-term securities under QE1 ($1.25 trillion in Mortgage-backed securities (MBS), $300 billion in Treasury securities, and $200 billion in debt securities issued by federal agencies). In late November 2010, the Fed announced its intention to make additional purchases of long-term government securities worth $600 billion under QE2, which ended in June 2011. QE3 was launched on September 13, 2012, with monthly purchases of $40 billion in MBS and a plan to increase long-maturity Treasury security holdings to $45 billion per month. By implementing a policy of quantitative easing, the Fed demonstrated its determination to keep the Fed interest rate low enough, for long enough. Figure 6 clearly illustrates the impact on interest rates of the three major quantitative easing measures implemented in the US after the 2007–2009 financial crisis.[5] Finally, in 2012, the Fed implemented an operation twist mechanism by lowering long-term interest rates while continuing to keep short-term interest rates near zero for a few years.

As mentioned above, by implementing quantitative easing, the Fed demonstrated its determination to keep the Fed rate low enough for long enough. If the markets had found this commitment credible, they should have anticipated low short-term interest rates for many months. They should also have anticipated long-term interest rates to fall, given that long rates reflect expected short-term interest rates. For example, according to Gagnon et al. (2010) and Chung et al. (2011), the Fed's injection of liquidity via its program of purchasing long securities between the end of 2008 and March 2010 have caused long-term rates to fall by around 50 basis points. Figure 6 supports the idea that quantitative easing measures caused short-term and long-term interest rates to decline.

[5] On the effects of QE policy, see Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011; D'Amico and King, 2013; D'Amico et al., 2012; Meaning and Zhu, 2011; Swanson, 2011; Hamilton and Wu, 2012; Meaning and Zhu, 2012; Engen et al., 2015; Sun et al., 2018; and Bonis et al., 2017.

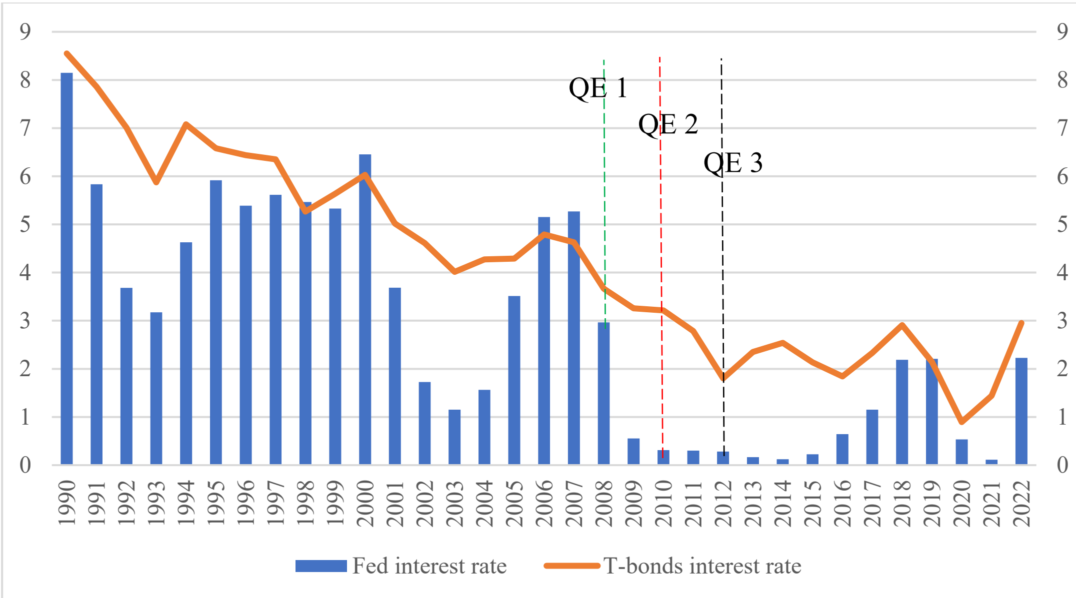

Figure 6: Trends in the Fed interest rate and 10-year T-bond interest rate
in the United States, 1990–2022

The three phases of the QE were the following: QE1 in 2008, QE2 in 2010, and QE3 in 2012. In addition, the Fed implemented an operation twist mechanism in 2012 to keep long-term interest rates low for an additional amount of time.
Data source: World Bank database.

Figure 6 also shows that the third quantitative easing measure, implemented in 2012, was very noteworthy because the 10-year T-bond reached a level of 2% for the first time, well below the 3% level. The 3% rate is often a guarantee on the minimum interest rate on 10-year T-bonds, used to calculate the value of variable annuities in the US (Berends et al., 2013). Indeed, variable annuity contracts often include a guarantee on the minimum interest rate used to calculate their value.[6] This guarantee entitles the insured to their accumulated value at a minimum interest rate of 3%. In other words, when the 10-year T-bond interest

[6] In 2010, 95% of life insurance contracts contained a minimum interest rate guarantee of 3% and 70% of annuity contracts had a minimum of 3% and higher. See Appendix E for more details. Variable annuities started in the 1980. They are like mutual funds offering tax advantage and minimum return guarantee. The minimum guarantee is a kind of long-term put option offered by insurers to their clients because variable annuities are much more risky than fixed annuities (Koijen and Yogo, 2021). The main source of revenue to insurers for managing this risk is long-term bonds. The risk management activity is partial, however, because bonds and options maturities are shorter than annuity maturities with guarantied revenue. This asset-liability mismatch may also increase risk volatility for insurers. An annual fee is charged to the insured for the option.

rate falls below 3%, as was the case between 2012 and 2022, the insured holding this put option continues to receive an investment return of 3%, with the difference being the interest rate management costs borne by the insurer. To cover the costs of integrated guarantees, insurers charge fees to policyholders. Table 8 presents the effect of the Fed interest rate on annuity sales. We observe a significant negative effect of the Fed interest rate on the variable annuity premiums sold after 2012. The fixed annuity market continued to growth, perhaps as a substitution effect between the two markets. These results were obtained from a panel of the 20 largest insurers that offered variable annuities during the 2008–2022 period. They account for about 90% of the market. More details on this data source are presented in Appendix E2.

Table 8: Effect of Fed interest rate on direct written premiums
in annuity markets, 2008–2022

Dependent variable: Direct written premiums Independent variable	Variable annuity Coefficient	Fixed annuity Coefficient
Post2012	-406.4*** (0.461)	-2.524*** (0.244)
Fed interest rate	34.18*** (0.296)	0.196 (0.207)
Post2012×Fed interest rate	-36.74*** (0.269)	1.979*** (0.658)
Annuity price index	11.72*** (0.021)	-0.040 (0.090)
Life expectancy	3.749*** (0.041)	-1.630*** (0.145)
Constant	-2,079*** (0.018)	137.2*** (0.061)
Insurer fixed effect	Y	Y
Year fixed effect	Y	Y
Double SE clustering	Insurer/Year	Insurer/Year
Observations	300	300
R-squared	0.796	0.731

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in the appendix.
Dependent variable and data source: Direct written premiums for individual annuity contracts issued by the 20 top-ranked annuity sales companies surveyed by LIMRA

Table 9: Effect of Fed interest rate on net written premiums
in annuity markets, 2010–2022

Dependent variable: Net written premiums Independent variable	Variable annuity Coefficient	Fixed annuity Coefficient
Post2012	-31.76*** (0.045)	0.333 (2.944)
Fed interest rate	2.545*** (0.017)	-8.419 (5.349)
Post2012×Fed interest rate	-2.745*** (0.021)	8.612 (5.174)
Annuity price index	-0.064*** (0.003)	0.005 (0.010)
Post2012×annuity price index	0.186*** (0.000)	-0.0225 (0.032)
Life expectancy	0.217*** (0.004)	-0.183 (0.207)
GDP ($ billion)	0.081** (0.027)	-0.0776 (0.077)
Constant	-7.983*** (0.001)	17.73 (12.27)
Insurer fixed effect	Y	Y
Year fixed effect	Y	Y
Double SE clustering	Insurer/Year	Insurer/Year
Observations	1,530	4,411
R-squared	0.863	0.587

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in the appendix.
Dependent variable and data source: Net written premiums for individual and group annuity contracts issued by insurance companies filing with the NAIC on the life, accident & health annual statement blank.

The interest rate factor seems to explain the drop in variable annuity sales during the post-2012 period. Life insurers with variable annuities had their stocks return with a negative exposure to interest rate during this period (Hartley et al., 2016). Many insurers stopped offering the option of minimum return guaranties; other left the market. Table 9 presents a robustness analysis of the results in Table 8 from a different panel of data. This panel from the NAIC (National Association of Insurance Commissioners) includes all insurers that offered non-negative net written premiums of annuities during the 2010–2022 period. Again, the Post2012 monetary policy had a negative effect on variable annuity sales.

In conclusion, the Fed interest rate factor had a negative effect on variable annuity sales in the post-2012 period. The interest rate differential (market interest rate and guaranteed 3% return), representing interest rate risk management costs assumed by life insurers during the post-2012 period, exerted downward pressure on the market.

6.2. Combined ratio and net gain from operations

We propose that the economic difficulties in the life insurance sector (particularly in variable annuity business) observed in the post-2012 period, explained by low interest rates, could have been a cause of the difference in the number of M&As of target insurers in the life insurance sector relative to the number of M&As of target insurers in the nonlife insurance sector. The new monetary policy motivated by the 2007–2009 financial crisis could have been the root of the economic and financial difficulties in the life insurance sector. Indeed, the very low interest rates may have significantly affected the investment benefits of annuities for insureds in the life insurance industry during the period under analysis and reduced the bid opportunities in the M&A market.

We consider that M&A transactions are positively correlated with the performance of targets' insurance business. The better the insurance business performs, the more M&As should occur in the insurance industry, particularly in the same business sector, as documented in the literature review. One of the best indicators of insurer performance is the combined ratio. This consists of the ratio of premiums paid (payments + operating expenses) to premiums collected (insurance policies and annuities sold). This indicator determines whether premiums collected are sufficient to cover expenses paid (including claims) and operating expenses. Clearly, the most obvious risk for insurers is that the premiums collected (sales) are insufficient to pay policyholders and cover expenses. Arguably, the higher the combined ratio, the more the premiums collected will be insufficient to cover claims paid and operating expenses, and the more the target insurer will find itself in financial difficulty. Moreover, the more the target insurer is in financial difficulty, the less it will be able to obtain interesting M&A conditions, which would reduce the number of M&A transactions. In other words, a high combined ratio should have a negative impact on M&As.

Figure 7 shows that the combined ratio in the life insurance sector has increased in recent years. The year 2012 represents the emblematic starting point for this increase. There are two potential explanations for this rise in the combined ratio, observed during the post-2012 period. First, payments may have grown faster than the premiums collected in the post-2012 period, which would push up the combined ratio. Second, premiums collected (sales) may have fallen significantly, making it difficult to cover total payments effectively.

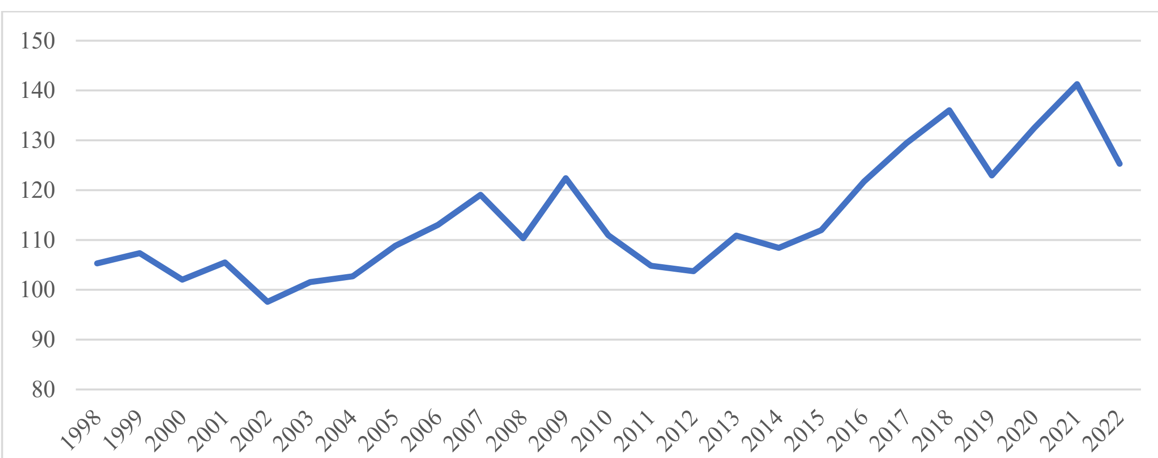

Figure 7: Trend in the combined ratio for the US life insurance sector, 1998–2022

Data source: NAIC. Formula of combined ratio = (claims costs + management expenses)/premiums collected.

We now study each component of the combined ratio. The drop in premiums is explained by a decline in sales of life insurance products after 2012. For example, a Life Insurance Marketing and Research Association (LIMRA) survey found that total annuity sales fell by 6% in the first quarter of 2013. Bernard and Moenig (2019) maintain that the decline in annuity sales began in 2013 because of the high fees charged to policyholders. They argue that financial advisors have resisted investing in annuities, especially variable annuities, because of the high fees charged on these products. We might suspect that the life insurance market as a whole experienced a downturn after 2012 due to the high costs of products sold.

The results in Table 10 show the positive influence of the Fed interest rate on the combined ratio after 2012. They confirm the results in Table 8 and Table 9 related to the reduction in sales, because coefficient of Total expenses after 2012 is not significant for the variable annuity line. The results clearly show that the negative shock in interest rates drove the combined ratio in the life insurance sector upward during the post-2012 period, a variation well explained by the Fed interest rate policy.

Results in Table 11 confirm the origin of the increase in the combined ratio after 2012 as related to the variation in annuity premiums. The interest rate policy reduced the usual negative impact of annuity premiums on the combined ratio in the variable annuity market. There was no significant effect in the fixed annuity market.

Table 10: Impact of Fed interest rate on the combined ratio
in the life insurance sector, 2010–2022

Dependent variable: Combined ratio Independent variable	Variable annuity Coefficient	Fixed annuity Coefficient
Lag Combined ratio	0.127	0.156**
	(0.117)	(0.057)
Post2012	7.290***	-0.375***
	(0.264)	(0.066)
Fed interest rate	-14.08***	-0.980***
	(0.887)	(0.246)
Post2012×Fed interest rate	13.90***	1.041***
	(0.868)	(0.244)
Annuity price index	-0.305***	0.004***
	(0.007)	(0.001)
Life expectancy	0.109***	-0.062***
	(0.026)	(0.005)
Total expenses ($ billion)	0.026**	0.004
	(0.009)	(0.003)
Post2012×total expenses ($ billon)	-0.003	0.017**
	(0.003)	(0.005)
Constant	41.59***	5.482***
	(1.021)	(0.258)
Insurer fixed effect	Y	Y
Year fixed effect	Y	Y
Double SE clustering	Insurer/Year	Insurer/Year
Observations	1,111	3,124
R-squared	0.524	0.490

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in the appendix. Data source: NAIC. We observe a positive effect of the Post2012 Fed interest rate on the life sector combined ratio in both the variable and fixed annuity markets with a greater effect in the variable annuity market.

Table 11: Determinants of the combined ratio in the life annuity market, 2010–2022

Dependent variable: Combined ratio Independent variable	Variable annuity Coefficient	Fixed annuity Coefficient
Lag Combined ratio	0.149	0.161**
	(0.0957)	(0.053)
Post2012	19.73***	13.23***
	(3.349)	(1.191)
Annuity premium ($ billon)	-10.93***	-7.716**
	(2.383)	(2.907)
Post2012×annuity premium ($ billon)	2.083*	-5.054
	(0.989)	(2.892)
Total expenses ($ billon)	11.86***	7.365**
	(2.278)	(2.735)
Post2012×total expenses ($ billion)	-2.132***	4.344*
	(0.543)	(2.231)
S&P 500 price index	-0.010***	-0.004***
	(0.001)	(0.000)
Constant	17.78*	83.14***
	(8.866)	(4.881)
Insurer fixed effect	Y	Y
Year fixed effect	Y	Y
Double SE clustering	Insurer/Year	Insurer/Year
Observations	1,111	3,124
R-squared	0.560	0.501

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in the appendix. The decrease in variable annuity premiums after 2012 reduces the negative basic effect of annuity premiums on the combined ratio.
Data source: NAIC.

Table 12 reinforces the preceding results by showing the negative impact of the Fed interest rate on the net gain from operations in the life annuity market. Net gains from operations are used in NAIC statements to measure profitability in the insurance business.

Table 12: Effect of Fed interest rate on net gain from operations
in the life annuity market, 2010–2022

Dependent variable: Net gain from operations Independent variable	Variable annuity Coefficient	Fixed annuity Coefficient
Lag Net gain from operating	-0.177 (0.203)	-0.163 (0.208)
Post2012	-16.23*** (1.162)	0.228*** (0.034)
Fed interest rate	42.85*** (3.195)	0.513*** (0.132)
Post2012×Fed interest rate	-42.32*** (3.148)	-0.597*** (0.126)
Annuity price index	0.761*** (0.011)	-0.008*** (0.000)
Life expectancy	-0.360*** (0.082)	0.093*** (0.010)
Total expenses ($ billon)	-0.112 (0.070)	0.054** (0.020)
Post2012×total expenses ($ billon)	0.070* (0.036)	-0.054 (0.031)
Constant	-99.01*** (7.204)	-6.361*** (0.770)
Insurer fixed effect:	Y	Y
Year fixed effect:	Y	Y
Double SE Clustering	Insurer/Year	Insurer/Year
Observations	1,111	3,124
R-squared	0.600	0.434

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in the appendix. We observe a significant negative effect of the Post2012 Fed interest rate on net gain from operations in both annuity markets with a greater effect in the variable annuity market.
Data source: NAIC.

6.3. Mergers and acquisitions

Table 13 shows a direct negative effect by the Fed interest rate on M&As during the post-2012 period in the life sector, while Table 14 confirms the DID analysis carried out in

Section 5, where Treated_L is equal to 1 for the life insurance sector and equal to 0 otherwise. These two results confirm the causally negative effect of the Fed monetary policy on M&As in the life insurance sector after 2012.

Table 13: Effect of Fed interest rate on mergers and acquisitions in the life insurance industry, 1990–2022

Dependent variable: M&As Life Independent variable	Coefficient
Post2012	-1.075***
	(0.112)
Fed interest rate	0.180***
	(0.010)
Post2012 × Fed interest rate	-0.381***
	(0.038)
GDP ($ billion)	0.163***
	(0.006)
Constant	1.511***
	(0.026)
State fixed effect	Y
Year fixed effect	Y
Observations	1,683
R-squared	0.514

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in the appendix. We observe a direct negative effect of the Fed interest rate on mergers and acquisitions in the life insurance industry.
Data source: SDC database.

Table 14: Impact of Fed interest rate on mergers and acquisitions in the two insurance sectors during the 1990–2022 period

Dependent variable : M&As in life and nonlife Independent variable	Coefficient
Post2012	-5.568*** (1.169)
TreatedL×Fed interest rate	0.017 (0.0174)
Post2012×TreatedL×Fed interest rate	-0.402*** (0.113)
GDP ($ billion)	0.349*** (0.070)
Constant	1.414*** (0.475)
State fixed effect:	Y
Year fixed effect:	Y
Double SE Clustering	State/Year
Observations	3,366
R-squared	0.533

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in Section 5 and in the appendix. This table confirms the DID analysis presented in Table 5 with an explicit indication that the Fed interest rate policy caused the treatment effect on mergers and acquisitions in the US insurance industry. Data source: SDC database.

6.4. Insurance business in the two sectors

6.4.1. Premiums to GDP

We have just demonstrated that it was the significant decline in premiums collected (sales) observed in the variable annuity line after 2012 that caused the combined ratio to rise in the post-2012 period, thus reducing the profitability of insurers in the life insurance sector. The decline in interest rates caused the decline in premiums collected in the variable annuity market and had a negative effect on M&As in the life sector. To conclude the analysis, we now focus on the link between the performance of the insurance business, measured by the ratio of premiums collected (sales), as a % of GDP, to M&A transactions. The ratio of premiums collected (sales) to GDP is known as a penetration rate and is often used by insurance professionals. It is an interesting indicator for assessing the importance of the insurance business sector in a country's economy. It shows whether insurance business as a proportion of the GDP is increasing or decreasing. In fast-growing economies, there is often an increase in demand for insurance products, which translates into a higher penetration rate. The growth of the insurance industry can then exceed that of the overall GDP. Conversely, a drop in demand for insurance products may translate into a lower penetration rate.

6.4.2. Analysis of the relationship between insurance business and M&A activity in the two insurance sectors

Our econometric results presented in Table 15 confirm the negative impact of life insurance business activity, as measured by premium % of the GDP, on M&A transactions after 2012. Thus, one could argue that the loss of the parallel M&A trend observed between the two insurance sectors in the post-2012 period is driven by a loss of the parallel trend in the insurance business market.

Figure 8 shows parallel time trends in the evolution of the premium % of the GDP for the two main insurance groups (life and nonlife) up to 2012 (especially from 2002 to 2012). Post-2012, insurance business diverges between the two groups. Figure 8 also indicates that insurance business declined as a proportion of the GDP for the life insurance sector from 2012 onwards, while it increased slightly as a proportion of the GDP for the nonlife insurance sector from 2012 onwards, thus creating a breakpoint in the parallel temporal trends in the evolution of insurance business for our two main insurance groups (life and nonlife) up to 2012. The stability in the nonlife insurance sector is explained, in part, by strong increases in premiums and reinsurance demand to compensate for climate risk losses (Dionne and Desjardins, 2022).

Table 15: M&A and Premium % of GDP in the life sector, 2001–2022

Dependent variable: M&A in the life sector Independent variable	Total life sector Coefficient	Annuity business line Coefficient	Life insurance line Coefficient
Post2012	-1.288*** (0.362)	-1.526*** (0.379)	-1.343*** (0.451)
Premium % of GDP	0.007** (0.003)	0.002 (0.005)	0.0119 (0.010)
Post2012×Premium % of GDP	-0.007*** (0.002)	-0.020*** (0.005)	-0.034*** (0.008)
Life expectancy	-0.282*** (0.017)	-0.262*** (0.010)	-0.293*** (0.009)
GDP ($ billion)	0.119*** (0.026)	0.127*** (0.024)	0.114*** (0.028)
Constant	22.490*** (0.107)	23.390*** (0.026)	25.39*** (0.050)
State fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
Double SE clustering	State/Year	State/Year	State/Year
Observations	1,122	1,122	1,122
R-squared	0.579	0.564	0.568

Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in the appendix. We observe a negative relationship between the variable Premium % of GDP and mergers and acquisitions in the life insurance sector, after 2012.
Data source: Report compiled annually by the NAIC. 1991-2019: Statistical compilation of annual statement information for life/health insurance companies compiled annually by the NAIC; 2020-2022: U.S. Life and A&H Insurance Industry: Annual Results.

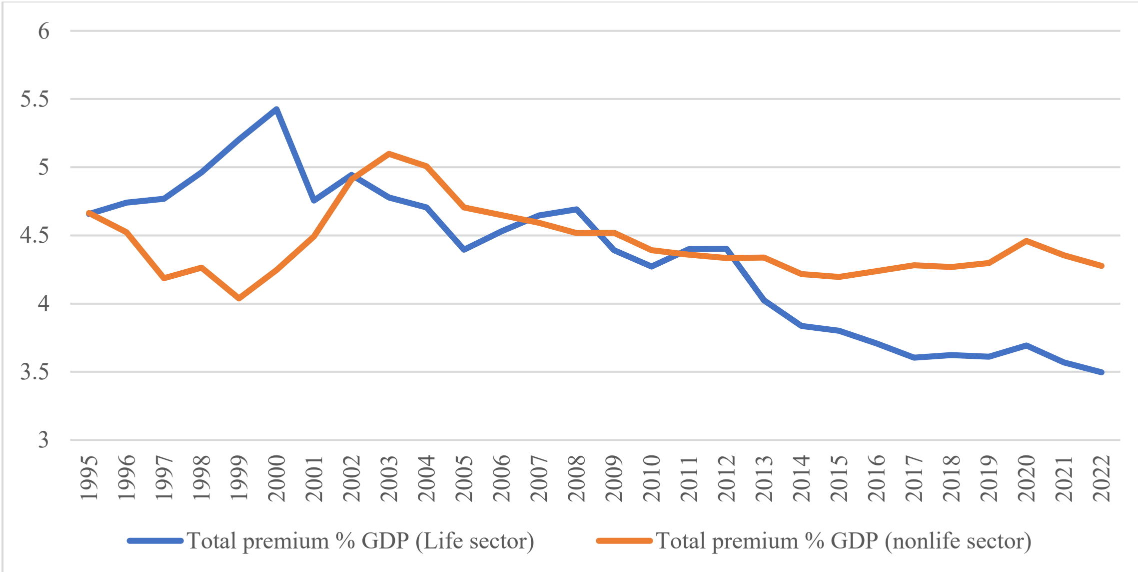

Figure 8: Evolution of the premium % of GDP ratio for the life and nonlife insurance sectors in the United States, 1995–2022

Data source: AM Best.

Conclusion

We analyze the evolution of M&As in the US insurance industry. We show that interest rates shocks related to the Fed monetary policy caused the loss of parallel trends in M&As between the life and nonlife sectors, after 2012. We also document that the Post2012 difference cannot be explained by climate risk events.

A significant drop in M&As was observed in the life insurance sector after 2012, and this drop was mainly explained by a decline in the variable annuity business. This result is due to a significant reduction in interest rates after the financial crisis, which increased the cost of risk management for life insurance companies offering variables annuities. It became too costly for the life insurance industry to offer the 3% minimum return guarantee on variable annuity products.

Low interest rates reduced the benefit of variable annuities and reduced the demand for these annuities. This unanticipated reduction in interest rates for a long period of time by the life insurance industry caused the low profitability of life insurers. Target life insurers became less attractive for mergers and acquisitions after 2012.

It seems that life insurers did not quickly anticipate the future reductions in interest rates and their potential consequences on their risk management activities. It was quite clear for many observers, however, that the Fed was willing to maintain its policy of low interest rates for an extended period after the 2007–2009 financial crisis (see Krishnamurthy and Vissing-Jorgensen, 2011, for example). Forward-looking risk management is still an open issue in the insurance industry, as we are now seeing with inflation risk.

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Appendix

Variables used in Section 6

Table 16: Variables, data sources and descriptions

Variable	Description	Measure	Data source
Total Expenses Annuity ($ billion) (Variable or Fixed annuity)	Annuity payments + Expenses Annuity Annuity payments of Annuity business line include benefit payments from annuity contracts and other contract payments. (Expenditures) Operating expenses of Annuity business line include commissions to agents, home-and field-office expenses, taxes, and investment expenses. (Expenditures)	Total Expenses	NAIC database
Variable Annuity contracts premium ($ billion) paid by insured	Variable annuity contracts allow the policy owner to allocate contributions into various subaccounts of a separate account based upon the risk appetite of the annuitant. The contributions can be invested in stocks, bonds or other investments. Income payments in the annuitization phase can be fixed or fluctuate with the investment performance of the underlying subaccounts of the separate account.	Variable Annuity premium	NAIC database LIMRA database
Fixed Annuity contracts premium ($ billion) paid by insured	For immediate fixed annuity contracts, annuitants receive a fixed income stream based, in part, on the interest rate guarantee at the time of purchase.	Fixed Annuity premium	NAIC database LIMRA database
Annuity business line contracts premium ($ billion)	Variable Annuity contracts premium + Fixed Annuity contracts premium.	Annuity business line premium	NAIC database LIMRA database
Producer Price Index (PPI) by Industry: Direct Life Insurance Carriers: Annuities (Index Dec 1998=100)	The Producer Price Index (PPI) program measures the average change over time in the selling prices received by domestic producers for their output.	Annuity price index	US Bureau of Labor Statistics database

Variable	Description	Measure	Data source
Short-term interest rates (%)	Short-term interest rates are the rates at which short-term borrowings are affected between financial institutions or the rate at which short-term government paper is issued or traded in the market. Short-term interest rates are generally averages of daily rates, measured as a percentage. Short-term interest rates are based on three-month money market rates where available. Typical standardized names are “money market rate” and “treasury bill rate”.	Fed interest rate	World Bank database
Combined ratio	Combined ratio is the sum of the payments and the expense to premiums received. (Expenditures ratio)	Combined ratio	NAIC database
Net gain from operations before dividends to policyholders and federal taxes	The Net Operating Gain is the sum of Net premium income, net investment income and miscellaneous income less benefit payments, expenses, reserve changes, but before policyholder dividends federal income taxes and realized capital gains/losses.	Net gain from operations	NAIC database
S&P 500 price index	The Standard and Poor’s 500, or simply the S&P 500, is a stock market index tracking the stock performance of 500 of the largest companies listed on stock exchanges in the United States. It is one of the most followed equity indices and includes approximately 80% of the total market capitalization of U.S. public companies.	S&P 500 price index	Macrotrends database
Life expectancy (number of years)	Life expectancy at birth used here is the average number of years a newborn is expected to live if mortality patterns at the time of its birth remain constant in the future.	Life expectancy	World Bank database
Gross domestic product ($ billion)	Gross domestic product (GDP) represents the sum of value added by all its producers. Value added is the value of the gross output of producers less the value of intermediate goods and services consumed in production, before accounting for consumption of fixed capital in production.	GDP	World Bank database

Additional appendices

Appendix A: Detailed analysis of some contributions on the insurance industry

The empirical literature on M&As in the insurance industry focuses primarily on examining the motivations for M&As, and the financial characteristics and operational efficiency of acquirers and targets pre- and post-consolidation. In this appendix, we review some articles in chronological order.

Chamberlain and Tennyson (1998) examine the empirical relevance of two hypotheses based on theories of information asymmetries and firm financing decisions: i) financial synergies are a primary motive for insurance mergers and acquisition activity in general, and ii) mergers motivated by financial synergies will be more prevalent in periods following negative industry capital shocks. The two hypotheses are investigated through an analysis of accounting ratios of acquisition targets during the period from 1980 to 1990 and an analysis of acquisition characteristics.

Firms can overcome funding problems through mergers and acquisitions between well-capitalized firms and poorly capitalized firms if information asymmetries are lower between targets and potential acquirers than they are between targets and the capital market. Chamberlain and Tennyson (1998) referred to these mergers as being driven by financial synergies.

The property-liability insurance industry is prone to capital shocks due to events such as natural disasters, changes in loss distributions, unexpected inflation or lower than expected investment returns, which affect many insurers simultaneously. Particularly, negative capital shocks will put many insurers in financial troubles, creating more opportunities for mergers based on financial synergies. The mergers motivated by financial synergies will be intensified after periods of negative capital shocks because of the increased information asymmetries due to the increased uncertainty about firm's values.

Chamberlain and Tennyson (1998) used a matched-pair research design to analyze the pre-merger performance, and the effects of merger on performance of the acquired firms. Each acquired company's performance is evaluated relative to the average performance of non-acquired subsidiaries which are of approximately the same size, and which operate in the same line of business as the acquired subsidiaries.

The results give weak support to the first hypothesis related to financial synergies. However, their results lead strong support to the hypothesis that financial synergies are an important motive for the merger transactions following the mid-1980s capital shock.

Cummins et al. (1999) empirically examine whether the scale economies and potential efficiency gains are a major driver for the mergers and acquisition in the insurance industry using a sample of 106 acquired life insurers during the period 1988-1994 The Malmquist index is employed to measure the productivity changes over time. Cummins et al. (1999) focuses their analysis on targets involved in the M&As by comparing the efficiency of these acquisition targets with firms that have not been targets of acquisition activity.

Overall, the results provide strong empirical evidence that target firms experienced significantly larger gains in efficiency than firms that were not implicated in M&A deals. This finding gives support to the evidence that acquisitions has improved the efficiency in the life insurance industry due to improvements in both revenue and cost efficiency and leading to a strong positive effect on profits for target firms.

Like in Cummins et al. (1999), Cummins and Xie (2008) analyze the productivity and efficiency effects of mergers and acquisitions in the US property-liability insurance industry. Their sample consists of 241 target companies that continued as viable operating entities following the acquisitions during the 1994-2003 period. They aim to determine the value implications of M&A activity for acquirers and targets using efficiency and productivity change measures. Authors also examine the firm characteristics associated with becoming an acquirer or target through probit regressions.

The principal finding is that poorly performing firms with low capitalization and poor underwriting performance are more likely to be takeover targets. Efficiency factors appear to have no significant impact on being target. These findings reveal that financial performance is a stronger predictor of being target in takeover deals.

Another finding is that large and rapidly growing profitable firms are more likely to be acquirers, suggesting that more large and profitable firms have more resources to engage in M&As and/or have stronger tax incentives to make acquisitions.

The efficiency variables are mostly insignificant for acquirers. However, the coefficient of technical efficiency is significant and negative, indicating that technically efficient firms are less likely be acquirers. Results also indicate that unaffiliated single firms and mutuals are less likely to be acquirers, indicating that groups are more likely to be acquirers. Finally, acquirers appear to have more exposure in the commercial long-tail business lines.

Boubakri et al. (2008) investigate whether M&A transactions create value for acquirers' shareholders and explore the different channels of how firm-level corporate governance mechanisms and cross-country differences in the legal environment and investor protection affect the long-run performance for acquirers. The sample consists of 177 M&A transactions over the sample period 1995-2000 where acquirers are US property-liability insurers and where targets could be U.S or foreign insurers.

Boubakri et al. (2008) measure the long run performance of acquirers by the 3-year buy and hold adjusted abnormal returns based on the market model. The results confirm a significant average positive abnormal return of 0.572 on the long run for acquirers, which is consistent with the evidence of a greater operating efficiency and a higher profitability during the post-acquisition three years. Results also suggest that M&A transactions involving not US targets, yield lower mean adjusted long run returns than domestic targets (0.247 and 0.636, respectively).

Pertaining to the deal characteristics, results indicate that mergers are less beneficial to acquirers and that tender offers are more value enhancing. Frequent acquirers are more likely to have higher returns in the long run due to the acquired experience to successfully integrate the target's activities into their own businesses. Moreover, results show that M&A transactions involving small size targets are more likely to enhance performance in the long run. Interestingly, the composite index of investor protection is negatively associated to the long run performance. Regarding the firm-level corporate governance, the results show that the board independence and block-holders' ownership yield unexpectedly negative and significant coefficients in relation to performance. Results related to the CEO characteristics indicate that the percentage of shares held by the CEO and the CEO duality

(CEO and president of the Board) are significantly and negatively related to the bidder's long run performance which is consistent with managerial entrenchment theory related to CEO ownership. The CEO tenure, the institutional ownership and the percentage of new members elected on the board seem to be insignificant determinants of the long run performance of the acquirers.

The objective of Cummins et al. (2015) is to examine the market value implication of M&A transaction in the global insurance industry on both target and acquiring firms. Cummins et al (2015) conduct an event study analysis to determine the market value effects of M&A deals where either the target or the acquirer is an insurance company and where the merger partner can be from any part of the financial industry.

This study is based on M&A transactions over the period 1990-2006, as reported in the Thomson Financial SDC Platinum database, where either the acquirer or target was an insurance company. Insurance companies were defined as all firms with four-digit Standard Industrial Classification (SIC) codes in the insurance industry.

The empirical methodology is based on an event study to capture the market reaction to the M&A transactions on both target and acquiring firms in a series of event windows surrounding the transaction dates. For each M&A transaction, the event study methodology computes the daily abnormal return using stock price data by subtracting the expected return from the actual return on each day during the event window. The predicted return on the stock is estimated by the standard market model using the stock's returns over the 250 trading-day period ending 30 days prior to the M&A event. The statistical significance is verified using three significance tests: the Patell Z-score, the standardized cross-sectional Z-score, and the generalized sign Z-score.

Overall, the event study reveals that M&A transactions are value enhancing for both acquirers and targets as expected. However the value effect for targets is larger. For example, the value gain measure by the average cumulative abnormal return is 10.8% for the targets and 0.52% for acquirers.

Cummins et al. (2015) also test the hypothesis stipulating that focusing M&As are more likely to create value for acquirers and targets than diversifying M&As by breaking down the M&A transactions into cross-industry and within-industry deals. Overall, the results show a larger market value gains for acquirers for M&A deals where both acquirers and targets are insurance compagnies.

Appendix B: Number of M&As by insurance sector

Table B1 (corresponding to Figure 4)

Year	Nonlife	Life
1990	30	26
1991	33	37
1992	43	34
1993	31	31
1994	35	47
1995	41	64
1996	55	60
1997	57	83
1998	86	86
1999	79	91
2000	54	48
2001	44	56
2002	40	57
2003	67	70
2004	78	50
2005	69	60
2006	69	74
2007	76	77
2008	61	54
2009	38	37
2010	41	59
2011	52	68
2012	41	39
2013	44	21
2014	53	21
2015	62	27
2016	46	11
2017	42	20
2018	49	28
2019	54	25
2020	54	16
2021	57	39
2022	95	35

Appendix C: Statistical tests

Table C1 presents three statistics and validation tests of the treatment date.

Table C1: Statistical descriptions (median, mean of the number of M&As) and validation tests of the treatment date

Period	1990-2009	Post-2009	1990-2012	Post-2012	1990-2022
Median	2	-23	3	-30.5	-2
Mean	2.8	-21.6154	3.8261	-31.3	-6.818
Student's test	1.015	-3.593	1.499	-8.111	-1.926
Median test	0.48	0.023	0.383	0.002	0.473
Wilcoxon test	1.028	-2.797	1.446	-2.805	-1.555

C1. Statistical test based on the mean (Student's test)

According to Table 3, the *t*-test statistic (Student's test) yields a value of 1.015 over the period of 1990 to 2009 and -3.593 over the post-2009 period. Given that the *t*-test value is less than 1.96 over the period of 1990 to 2009, the null hypothesis (H0) is not rejected. In addition, because the *t*-test value is lower than -1.96 over the post-2009 period, the null hypothesis (H0) is rejected. The year 2009 is therefore retained by our *t*-test criterion as the treatment date for our DID method. Further, Table 3 shows that the *t*-test statistic yields a value of 1.499 over the 1990 to 2012 period and -8.111 over the post-2012 period. Our *t*-test statistic criterion cannot discriminate between the two years and between the two potential interpretations.

C2. Statistical test based on the median

This test was proposed by Snecdecor and Cochran (1989). Based on this test, the analyze of the null hypothesis (H0) that the difference between the median number of M&As of target nonlife insurers and the median number of M&As of target life insurers is equal to 0.

Our treatment date decision criterion is to test the null hypothesis (H0) that the median number of M&As in the nonlife sector and the median number of M&As in the life sector are statistically similar over the period of 1990 to the end of the candidate date (2009 or 2012) on the one hand, and, on the other hand, to test the null hypothesis (H0) that the median number of M&As in the nonlife sector and the median number of M&As in the life sector are statistically different over the post-treatment date period (post-2009 or post-2012) due to the treatment effect.

Table 3 reports a *p*-value of 0.481 over the period of 1990 to 2009 and 0.023 over the post-2009 period. Because the *p*-value is above the critical threshold of 5%, the null hypothesis is not rejected. In addition, because the *p*-value is lower than the 5% threshold over the post-2009 period, the null hypothesis (H0) is rejected. The year 2009 is therefore retained by our median-based statistical test as the treatment date for our DID method. Further, Table 3 shows a *p*-value of 0.383 over the 1990 to 2012 period and 0.002 over the post-2012 period. We conclude that the median number of M&As in the nonlife sector and the median number of M&As in the life sector are statistically similar over the period of 1990 to 2012 and statistically different over the post-2012 period. Our test based on the median cannot discriminate between the two dates.

C3. Statistical test based on distributions

We test the null hypothesis (H0) that the distributions of the number of M&As per year of target nonlife insurers and the number of M&As per year of target life insurers are close.

According to Table 3, the Wilcoxon test statistic yields a value of 1.028 over the period of 1990 to 2009 and -2.797 over the post-2009 period. Because the Z-test value is less than 1.96 over the period of 1990 to 2009, the null hypothesis (H0) is not rejected. In addition, because the Z-test absolute value is greater than 1.96 over the post-2009 period, the null hypothesis (H0) is rejected. We can therefore conclude that the distribution of the number of M&As in the nonlife sector and the distribution of the number of M&As in the life sector are statistically similar over the period of 1990 to 2009 and statistically different over the post-2009 period. Table 3 also shows that the Wilcoxon test statistic yields a value of 1.446 over the 1990 to 2012 period and -2.805 over the post-2012 period. We therefore conclude that the distribution of the number of M&A in the two industries are statistically similar over the period of 1990 to 2012 and statistically different over the post-2012 period. Our test of the distribution-based statistic cannot discriminate between the two dates.

Appendix D: Robustness checks of the DID analysis

Table D1 reproduces the basic estimation[7] results of the Average Treatment on Treated (ATT) ($Treated_L$×Post2012) using the SDID, DID, and SC models where the treated group is the life sector, and the control group is the nonlife sector. The outcome is the number of M&As per State-Year during the period 1990-2022. The treatment indicator is a dummy variable that take the value of 1 for life insurers during the years 2013-2022 and 0 otherwise. The results show a significant negative impact on the life sector for the three methods. In comparison with the DID estimator, the SDID gives a very close estimation of the ATT. However, the SC method yields an absolute ATT estimation relatively higher in absolute value.

Table D1: Estimation of the ATT using the DID, SDID, and SC models for the period 1990–2022

	(1)	(2)	(3)
Number of M&As by State-Year	SDID	SC	DID
$Treated_L$×Post2012	-0.689*** (0.108)	-0.712*** (0.150)	-0.689*** (0.117)
Constant[8]	Y	Y	Y
State fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	3,366	3,366	3,366

*** p<0.01.

[7] We use the user-written Stata command *sdid* developed recently by Clarke et al (2023). This command allows the estimation of the SDID and the SC models besides the standard DID.

[8] The estimation is done within the optimization routines in Mata and only the ATT estimation is reported by the Stata command. Additional data are presented in Appendix E.

Figures D1 and D2 give the M&As by State-Year trends for both the treated and the control groups, and time-specific weights, for the SDID and SC, respectively. The weights used to average pre-2012 time periods are at the bottom of the graphs.

Figure D1

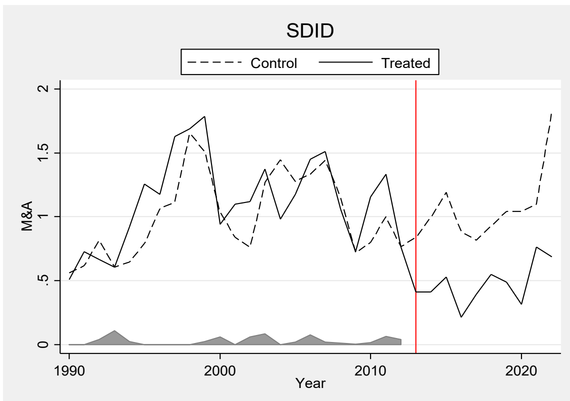
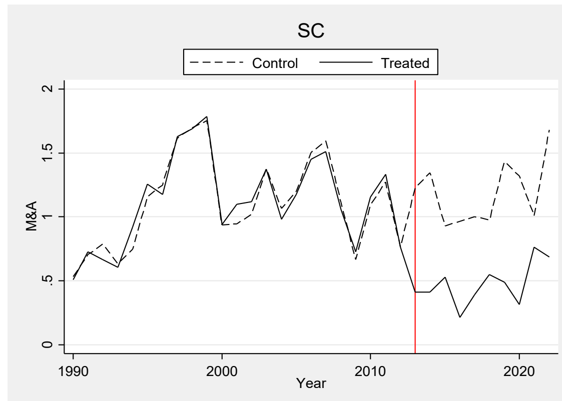


Figure D2



The figures show trends in M&A over time for the life insurance sector and the relevant weighted average of M&A in the nonlife insurance sector, with the weights used to average pretreatment time periods at the bottom of the graphs. The red line is for the year 2013 which indicates the beginning of the post-treatment period. 2012 is the treatment year.

These two figures illustrate how each method operates. SC reweights the States on the control group (nonlife sector) so that the weighted of M&A per year for these States match the M&As per year of the treated group (life sector) as close as possible during the pre-2012 periods, and then attributes any post-2012 divergence of number of M&A in the life sector from this weighted average to the choc during 2012. In contrast, the SDID reweights the control group units to make their outcome time trend parallel to the treated group during the pre-periods, but not necessarily identical as with the SC method. Subsequently, a DID analysis is applied to this reweighted panel. Time weights allow to select a subset of the pre-2012 time periods so that the weighted average of historical M&As per year for the control units predicts average M&As per year during the post-periods for the same control units, up to a constant.

Figures D3 and D4 show the control unit-specific weights coming from the estimation of the SDID and SC, respectively. The figures show the State-by-State adjusted outcome difference, namely the difference between the average number in the number of M&As per State-Year for treated group and the average number of M&As per year for the designed State. The estimated ATT, indicated by the horizontal line, is the weighted average of these differences. The States' weights are indicated by the dot size. Observations with zero weight are denoted by a × symbol. States are ordered alphabetically.

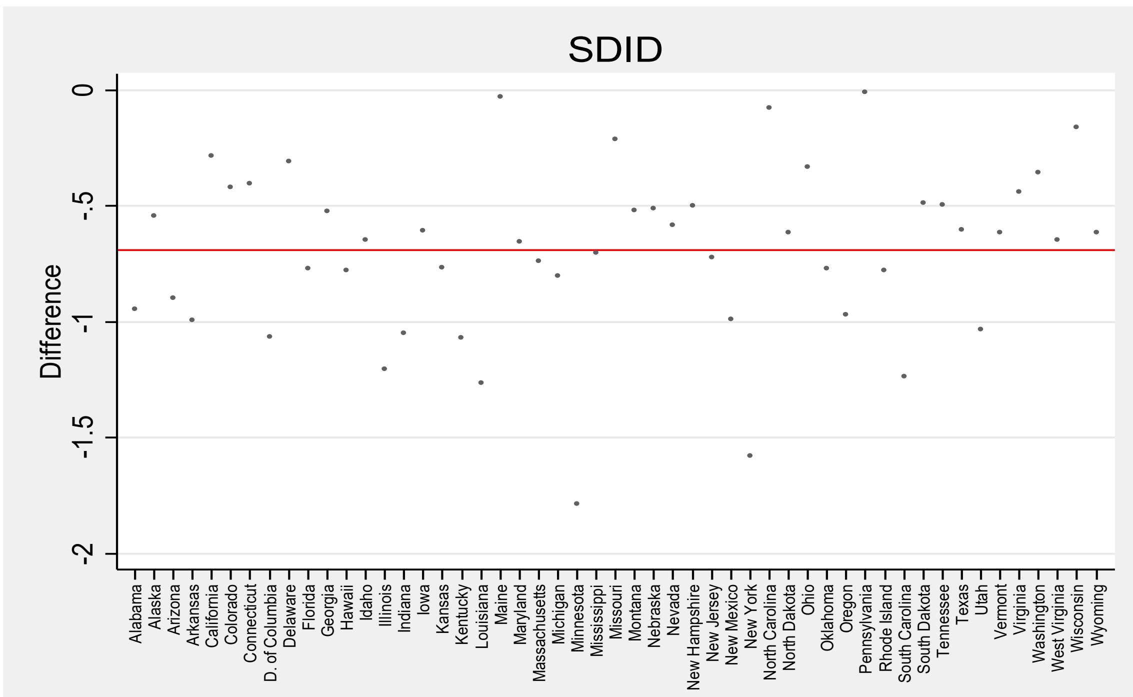


Figure D3: Unit-specific weights

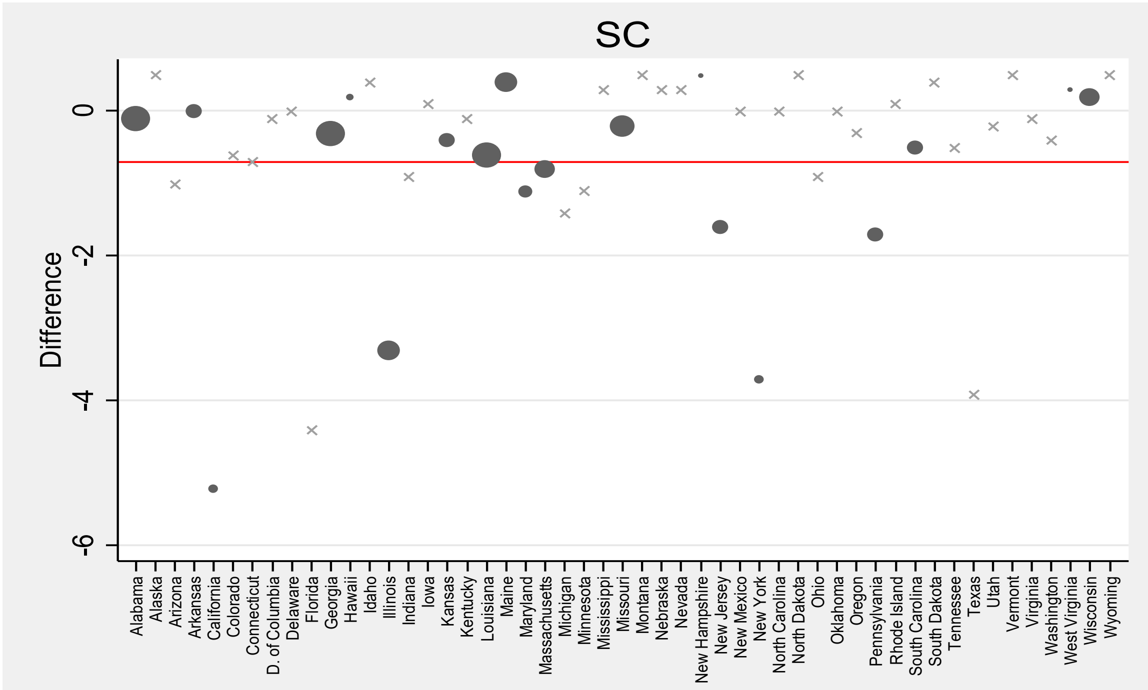


Figure D4: Unit-specific weights

We observe that the SDID method does not give any State particularly high influence. In contrast, the weights by the SC methods are very sparse and give high influence for some States (Arizona, Louisiana, Georgia).

Subsequently, we estimate a new empirical specification of the SDID and SC estimation by adding time variant covariates. We add the following covariates by State-Year for the treated and the control groups: direct written premiums, number of domestic insurers, number of foreign insurers, number of climate events, and the insured losses.[9]

Table D2 reports the estimation results of the Average Treatment on Treated (ATT) using the SDID and SC methods, alongside the standard DID, by adding the above indicated

[9] Parameters on covariates are estimated within the optimization routines in Mata. We use the *Projected* option suggested by Kranz (2022), where the impact of covariates is projected out using a baseline regression of the outcome on covariates and state fixed effects only in units where the treatment status is equal to zero.

covariates in the estimations. The estimation period is now from 2001 to 2022 due to the lack of detailed data for the direct written premium for each sector: Life, Health, and P&C, before 2001. Comparatively to the estimated effect reported in Table D1, we observe that adding covariates increases in absolute value the estimated ATTs with the SDID and SC methods which are now around -0.76 and -0.91 respectively. The DID estimation gives a notably lower treatment effect in absolute value. However, differences in the estimated ATTs reported in Tables D1 and D2 are not explained only by adding covariates but also by different time frames for the two estimations. Specifically, the SDID method which attributes different weights for pre-treatment periods. We investigate this issue later.

Table D2: Estimation of the ATT using the SDID and SC models:
Adding covariates from 2001 to 2022

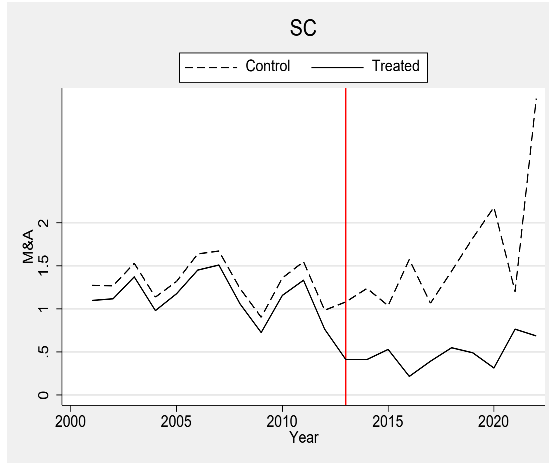
	(1)	(2)	(3)
Number of M&As by State-Year	SDID	SC	DID
$\text{Treated}_{L}\times\text{Post2012}$	-0.763***	-0.914***	-0.610***
	(0.200)	(0.336)	(0.194)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	2,244	2,244	2,244

*** p<0.01.

The following two Figures D5 and D6 give the M&As by State-Year trends for both the treated and the control groups, and time-specific weights, for the SDID and SC, respectively. The estimations are with covariates.

Figure D5

Figure D6



The figures show trends in M&A over time for the life insurance sector and the relevant weighted average of M&A in the nonlife insurance sector, with the weights used to average pretreatment time periods at the bottom of the graphs. The red line is for the year 2013 which indicates the beginning of the post-treatment period. 2012 is the treatment year.

Figures D7 and D8 show the control unit-specific weights coming from the estimation of the SDID and SC with covariates, respectively.

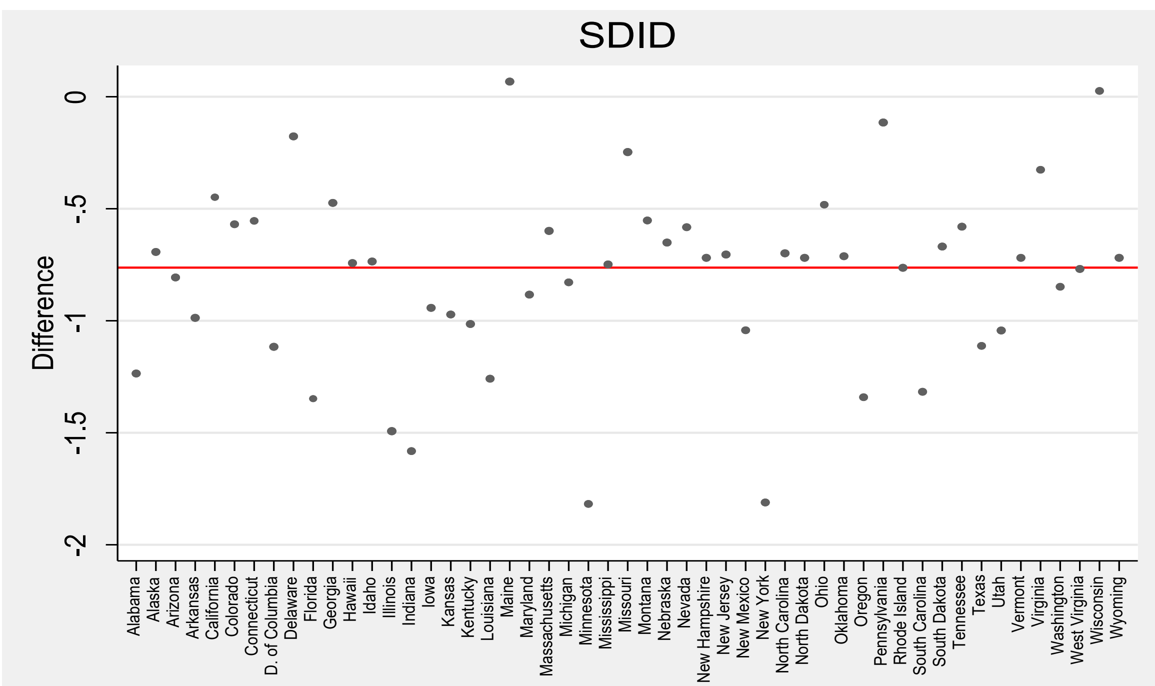


Figure D7: Unit-specific weights with covariates

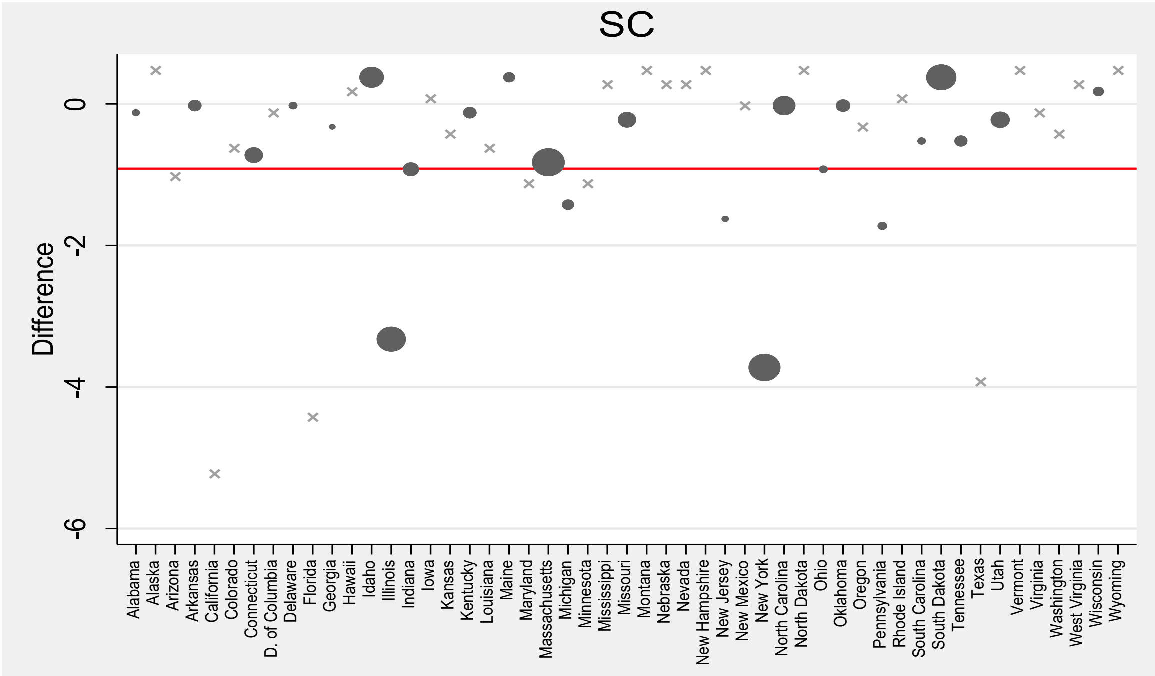


Figure D8: Unit-specific weights with covariates

We observe again that the SDID method does not give any State particularly high influence as with the estimation without covariates. On the contrary, the weights by the SC method give high influence for some States (New York, Illinois, Massachusetts, Texas). It is worth noting that these States have different weights with the baseline estimation without covariates. So, adding covariates could change the weighting scheme especially for the SC model.

Going further, we now gauge the impact of adding covariates on the estimation of the treatment effects. We then run the same estimation as in Table D2 for the same period 2001-2022, but without the covariates. The estimation results are reported in Table D3 and show that the estimated treatment effect for the SDID, the SC and the DID methods are quantitatively higher in absolute value from the estimated effects reported in Table D2, namely with covariates. It appears that the estimated treatment effect by the three methods is sensitive to the conditioning on time varying covariates. Remarkably, the results reported in Table D1 and D3 show a relative difference in the estimated treatment effects over the two time periods 1990-2022 and 2001-2022.

Table D3: Estimation of the ATT using the SDID and SC models:
Without covariates from 2001 to 2022

	(1)	(2)	(3)
Number of M&As by State-Year	SDID	SC	DID
$Treated_L \times Post2012$	-0.797***	-0.948***	-0.655***
	(0.125)	(0.194)	(0.135)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	2,244	2,244	2,244

*** p<0.01.

In the previous estimations, the control group consists of nonlife sector. Now, we decompose this control group into two separate sectors: Health and P&C. We estimate SDID, SC and DID methods using these two separate control groups. Table D4 reports the estimations results with this new data setting. In comparison with the baseline estimation reported in Table D1, Table D4 shows an ATT notably lower in absolute value for the SDID and SC methods. However, the increase in the estimated effect is stronger for the SC method: the ATT goes from -0.71 (Table D1) to -0.61. Interestingly, the DID estimator appears to be insensitive to the data setting and yields a similar average treatment effect than the baseline estimation, namely with only one control group.

Table D4: Estimation of the ATT using the SDID and SC models: Two control groups for the period 1990 to 2022

	(1)	(2)	(3)
Number of M&As by State-Year	SDID	SC	DID
$Treated_L$×Post2012	-0.651***	-0.614***	-0.680***
	(0.135)	(0.166)	(0.112)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	5,049	5,049	5,049

*** p<0.01.

Figures D9 and D10 show the M&As by State-Year trends for the treated group and the control groups, and time-specific weights, for the SDID and SC, respectively.

Figure D9

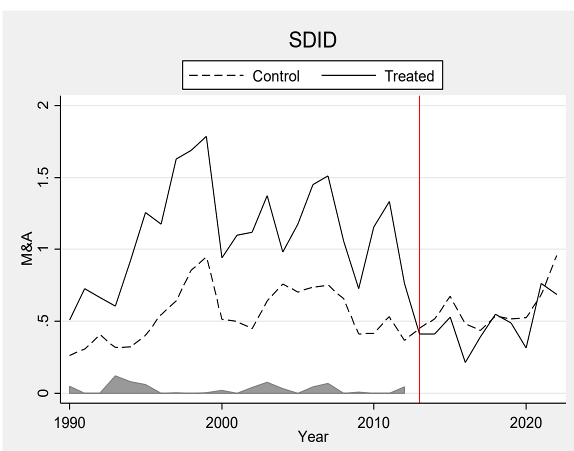
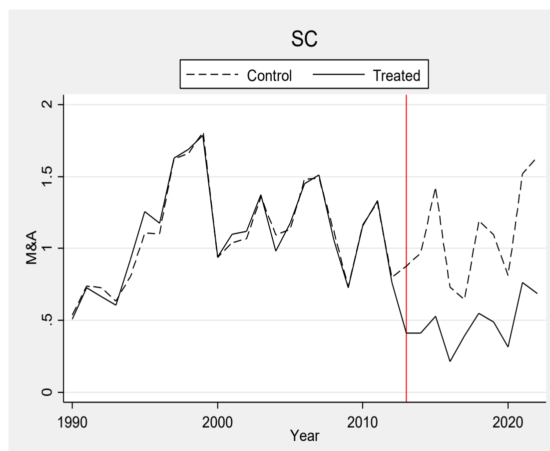


Figure D10



The figures show trends in M&A over time for the life insurance sector and the relevant weighted average of M&A in the nonlife insurance sector, with the weights used to average pretreatment time periods at the bottom of the graphs. The red line is for the year 2013 which indicates the beginning of the post-treatment period. 2012 is the treatment year.

Additional figures (not reported) indicating the control unit-specific weights coming from the estimation of the SDID and SC with the new data setting (two control group), show again that the SDID estimation gives approximately similar weights to the different States. However, the SC model puts more influence for some states.

As before, we add covariates to this new data setting and re-estimate the SDID, SC and the DID models. For each State-Year observation from 2001 to 2022, we add the same covariates discussed previously: direct written premiums, number of domestic insurers, number of foreign insurers, number of climate events, and the insured losses. It is worth noticing that we have the life sector as our treated group and the health and P&C sectors as our control groups. For each sector, we then collect the premiums and the number of insurers by State-Year for the 2001–2022 period.

Table D5 reports the ATT estimation results with covariates and two control groups and show a statistically significant treatment effect but with lower magnitude in absolute value as compared to the previous estimation (Table D4) and the baseline estimation (Table D1). Noticeably, the ATT is much lower with the SC estimation.

Table D5: Estimation of the ATT using the SDID and SC models: Two control groups and with covariates for the 2001–2022 period

Number of M&As by State-Year	(1) SDID	(2) SC	(3) DID
$Treated_L$×Post2012	-0.601***	-0.545***	-0.629***
	(0.151)	(0.180)	(0.132)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	3,366	3,366	3,366

*** p<0.01.

Figures D11 and D12 show the M&As by State-Year trends for the treated group and the control groups, and time-specific weights, for the SDID and SC, respectively.

Figure D11

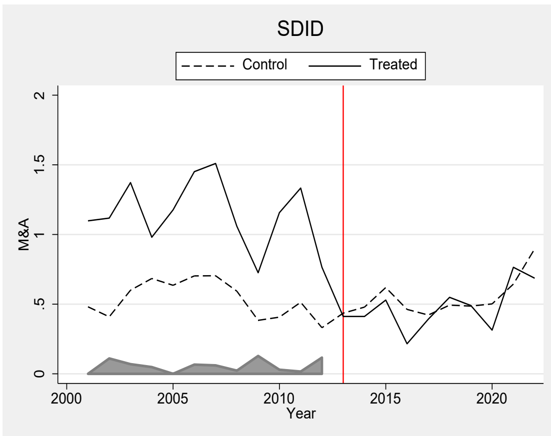
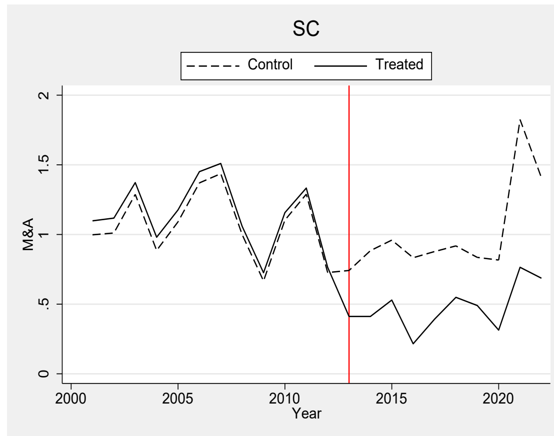


Figure D12



The figures show trends in M&A over time for the life insurance sector and the relevant weighted average of M&A in the nonlife insurance sector, with the weights used to average pretreatment time periods at the bottom of the graphs. The red line is for the year 2013 which indicates the beginning of the post-treatment period. 2012 is the treatment year.

We estimate the same empirical specification as in Table D5, with two control groups, but without covariates to determine how the estimated treatment effect is sensitive to the controlling for the time varying covariates. The results are reported in Table D6 and indicate relatively higher estimated treatment effects in absolute value for the SDID and DID models, and slightly lower absolute effect for the SC model, as compared to the estimations in Table D5.

Table D6: Estimation of the ATT using the SDID and SC models: Two control groups and without covariates for the 2001–2022 period

Number of M&As by State-Year	(1) SDID	(2) SC	(3) DID
$Treated_L \times Post2012$	-0.643***	-0.524**	-0.674***
	(0.130)	(0.208)	(0.100)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y
Year fixed effect	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	3,366	3,366	3,366

*** p<0.01.

In sum, we find that the baseline estimation, namely with one control group and without covariates, gives qualitatively similar treatment effects by the two methods, SDID and DID, and slightly different effects by the SC methods. With two separate control groups and without covariates, the DID estimation yields a similar treatment effect as in the baseline estimation. However, the SDID and the SC give higher ATT in absolute value. Interestingly, adding time-varying covariates into the estimation reduces slightly the treatment effects for the three estimation methods and with either one or two control groups, and do not modify the main conclusions of the experiment analysis.

Overall, we observe that the SDID and DID estimations give relatively similar results for the treatment effects in baseline estimation and in the estimations with two control groups. In addition, it appears that the SDID and DID estimators for the treatment effect are more stable than the SC estimation which varies from -0.95 to -0.52 depending on the empirical setting. Table D7 summarizes the estimated average treatment effects for the different empirical settings: one/two control groups, different periods, and with/out covariates.

Table D7: Estimation summary

	Empirical setting	SDID	SC	DID
Table D1	1990-2022 One control group Without covariates	-0.689***	-0.712***	-0.689***
Table D2	2001-2022 One control group With covariates	-0.763***	-0.914***	-0.609***
Table D3	2001-2022 One control group Without covariates	-0.797***	-0.948***	-0.655***
Table D4	1990-2022 Two control groups Without covariates	-0.651***	-0.614***	-0.680***
Table D5	2001-2022 Two control groups With covariates	-0.601***	-0.545***	-0.629***
Table D6	2001-2022 Two control groups Without covariates	-0.643***	-0.524**	-0.674***

*** p<0.01.

Appendix E: Data from different sources

E1 Variables used in Kranz analysis presented in Appendix D

We added the following covariates by State-Year for the estimations in Appendix D: direct written premiums, number of domestic insurers, number of licensed foreign insurers, number of climate events, and the insured losses from climate events. Direct written premiums is for a market size effect and number of insurers is for the competitivity of different markets in different states.

Direct written premiums by state-year for all claims are taken from the state and Countrywide Insurance Data section of the Statistical Compilation of Annual Statement Information Report annually produced by the NAIC for the three insurance sectors, Life and Annuity, Property and Casualty, and Health, separately. The number of domestic and foreign insurers by state-year are taken from the Examination and Oversight section of The Insurance Department Resources Report published annually by the NAIC. Domestic Insurer is an insurance company domiciled in the state in which the business is written. Foreign Insurer is an insurance company whose state of domicile is other than the state in which the company is writing business. Climate events and the insured losses by State-Year are from the Verisk Analytics Inc affiliated to the Insurance Services Office Inc. A climate event is an extreme weather event which is likely to cause US$25,000,000 or more in total insured property losses and is likely to affect a significant number of property and casualty insurance policyholders, based on the Verisk judgement. Insured losses are insured property losses paid by property and casualty insurance companies to policyholders for climate risk events only.

Table E1 shows summary statistics for these covariates for the treated (life insurance sector) and the control group (nonlife insurance sector) over the period 2001-2022. Observations are for State-Year.

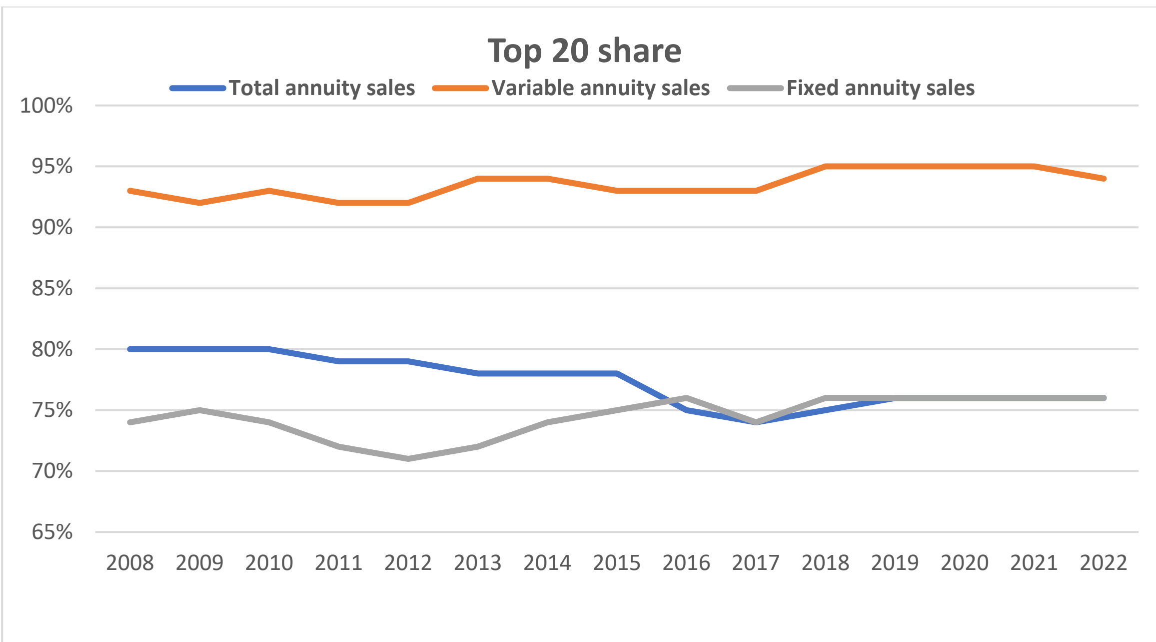
Table E1: Summary statistics Kranz analysis: 2001-2022

	Treated group				Control group			
Variables	Obs	Mean	Median	SD	Obs	Mean	Median	SD
Direct written premiums ($ billion)	1,122	14.840	9.000	17.616	1,122	20.727	13.000	24.175
Number of domestic insurers	1,122	20.348	12.000	30.977	1,122	67.749	39.500	68.745
Number of foreign insurers	1,122	438.322	445.000	79.208	1,122	822.844	841.000	144.665
Number of climate events	1,122	3.487	2.000	3.588	1,122	3.487	2.000	3.588
Insured losses ($ million)	1,122	633.748	107.000	2575.896	1,122	633.748	107.000	2575.896

E2 Panel of top 20 insurance companies

We use data related to the top 20 insurance companies reported annually in the LIMRA US Individual Annuities Sales Survey[10] for the 2008–2022 period. LIMRA produces a ranking of the top 20 companies for the annual total individual annuity sales, annual individual variable annuity sales and annual individual fixed annuity sales.

The following figure gives the top 20 share of the annuity sales and shows, remarkably, that the top 20 share for variable annuity sales is higher than 90 percent. The top 20 share for fixed annuity sales oscillates around 75 percent.



The following table shows the summary statistics of the individual annuity sales for the top 20 insurers during the period 2008-2022.

[10] These sales surveys can be retrieved from the LIMRA web site: https://www.limra.com/en/newsroom/fact-tank/.

Table E2: Summary statistics for top 20 insurers (in $ billion)

Variable	Obs	Mean	Median	SD
Total annuity sales	300	9.225	8.141	5.273
Variable annuity sales	300	5.849	4.209	5.143
Fixed annuity sales	300	4.220	3.242	2.967

The following three tables shows the top 20 ranking for the years from 2008 to 2022 and for the total annuity sales, fixed annuity sales and variable annuity sales.

Table E3: Top 20 ranking: total individual annuity sales

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	MetLife	MetLife	Prudential Annuities	MetLife	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	AIG Companies	Jackson National Life	Jackson National Life	Jackson National Life	New York Life
2	AIG	Prudential Annuities	MetLife	Prudential Annuities	Prudential Annuities	AIG Companies	AIG Companies	AIG Companies	AIG Companies	AIG Companies	Jackson National Life	AIG Companies	AIG Companies	AIG Companies	Athene Annuity & Life
3	ING	TIAA-CREF	Jackson National Life	Jackson National Life	MetLife	Lincoln Financial Group	Lincoln Financial Group	Lincoln Financial Group	TIAA	New York Life	New York Life	Lincoln Financial Group	New York Life	Equitable Financial	Corebridge Financial
4	TIAA-CREF	Jackson National Life	TIAA-CREF	AIG Companies	TIAA-CREF	TIAA-CREF	Allianz Life of North America	TIAA-CREF	New York Life	TIAA	Lincoln Financial Group	New York Life	Lincoln Financial Group	Allianz Life of North America	Massachusetts Mutual Life
5	Lincoln Financial Group	AIG	AIG Companies	TIAA-CREF	Lincoln Financial Group	MetLife	TIAA-CREF	New York Life	Allianz Life of North America	AXA US	Allianz Life of North America	Allianz Life of North America	Equitable Financial	New York Life	Equitable Financial
6	AXA Equitable	Lincoln Financial Group	Lincoln Financial Group	Lincoln Financial Group	AIG Companies	Prudential Annuities	New York Life	Allianz Life of North America	AXA US	Nationwide	AXA US	Equitable Financial	Allianz Life of North America	Lincoln Financial Group	Jackson National Life
7	John Hancock	New York Life	Allianz Life of North America	Allianz Life of North America	AXA Equitable	AXA US	Prudential Annuities	MetLife	Lincoln Financial Group	Allianz Life of North America	TIAA	Nationwide	TIAA	Nationwide	Allianz Life of North America
8	Prudential Annuities	ING	New York Life	Nationwide Financial	Allianz Life of North America	New York Life	Transamerica	AXA US	Prudential Annuities	Lincoln Financial Group	Nationwide	Prudential Annuities	Brighthouse Financial	Massachusetts Mutual Life	Lincoln Financial Group
9	New York Life	RiverSource Life Insurance	RiverSource Life Insurance	New York Life	New York Life	Allianz Life of North America	AXA US	Prudential Annuities	MetLife	Pacific Life	Pacific Life	TIAA	Sammons Financial Companies	Athene Annuity & Life	Pacific Life
10	Hartford Life	Allianz Life	ING	AXA Equitable	Pacific Life	Transamerica	MetLife	Nationwide	Nationwide	Prudential Annuities	Prudential Annuities	Pacific Life	Athene Annuity & Life	Brighthouse Financial	Nationwide
11	Jackson National Life	John Hancock	AXA Equitable	RiverSource Life Insurance	Nationwide Financial	Pacific Life	Nationwide	Transamerica	American Equity Investment Life	Global Atlantic Financial Group	Global Atlantic Financial Group	Global Atlantic Financial Group	Nationwide	Pacific Life	Brighthouse Financial
12	RiverSource Life Insurance	AEGON USA	AVIVA	AEGON USA	RiverSource Life Insurance	Nationwide Life	Pacific Life	American Equity Investment Life	Pacific Life	Athene Annuity & Life	Athene Annuity & Life	Athene Annuity & Life	Prudential Annuities	TIAA	Global Atlantic Financial Group
13	AEGON USA	AXA Equitable	Nationwide Financial	American Equity Investment Life	Transamerica	Security Benefit Life	Forethought Annuity	Pacific Life	Global Atlantic Financial Group	RiverSource Life Insurance	Massachusetts Mutual Life	Brighthouse Financial	Pacific Life	Global Atlantic Financial Group	Sammons Financial Companies
14	Pacific Life	Pacific Life	American Equity Investment Life	Pacific Life	AVIVA	RiverSource Life Insurance	RiverSource Life Insurance	Forethought Annuity	Athene Annuity & Life	Great American	Great American	Massachusetts Mutual Life	Massachusetts Mutual Life	Prudential Annuities	Fidelity & Guaranty Life
15	Allianz Life	AVIVA	Pacific Life	AVIVA	American Equity Investment Life	American Equity Investment Life	Security Benefit Life	RiverSource Life Insurance	Midland National	American Equity Investment Life	Brighthouse Financial	American Equity Investment Life	Global Atlantic Financial Group	Fidelity & Guaranty Life	Western Southern Group
16	Aviva	Nationwide Life	AEGON USA	Protective Life	Security Benefit Life	Great American	American Equity Investment Life	Symetra Financial	RiverSource Life Insurance	Brighthouse Financial	RiverSource Life Insurance	Great American	RiverSource Life Insurance	RiverSource Life Insurance	TIAA
17	Nationwide Life	Sun Life Financial	John Hancock	Thrivent Financial for Lutherans	Protective Life	Massachusetts Mutual Life	Thrivent Financial	Great American	Transamerica	Symetra Financial	American Equity Investment Life	RiverSource Life Insurance	Security Benefit Life	Sammons Financial Companies	Symetra Financial
18	Genworth Financial	Hartford Life	Sun Life Financial	Sun Life Financial	Thrivent Financial for Lutherans	Thrivent Financial for Lutherans	Great American	Thrivent Financial for Lutherans	Great American	Transamerica	Principal Financial Group	Transamerica	Fidelity & Guaranty Life	American Equity Investment Life	Prudential Annuities
19	Principal Life	American Equity Investment Life	Thrivent Financial for Lutherans	Great American	Great American	Protective Life	Symetra Financial	Midland National	Symetra Financial	Thrivent Financial for Lutherans	Symetra Financial	Symetra Financial	American Equity Investment Life	Symetra Financial	USAA Life
20	Allstate Financial	Massachusetts Mutual Life	Protective Life	John Hancock	Massachusetts Mutual Life	Symetra Financial	Massachusetts Mutual Life	Principal Financial Group	Thrivent Financial for Lutherans	Security Benefit Life	Transamerica	Fidelity & Guaranty Life	Great American	Security Benefit Life	Security Benefit Life

Table E4: Top 20 ranking: individual variable annuity sales

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	TIAA-CREF	Prudential Annuities	Prudential Annuities	MetLife	Prudential Annuities	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	Jackson National Life	Equitable Financial
2	MetLife	MetLife	MetLife	Prudential Annuities	Jackson National Life	Lincoln Financial Group	Lincoln Financial Group	TIAA-CREF	TIAA	TIAA	AXA US	Equitable Financial	Equitable Financial	Equitable Financial	Jackson National Life
3	ING	TIAA-CREF	Jackson National Life	Jackson National Life	MetLife	TIAA-CREF	AIG Companies	Lincoln Financial Group	AXA US	AXA US	TIAA	TIAA	Lincoln Financial Group	Lincoln Financial Group	Lincoln Financial Group
4	AXA Equitable	Jackson National Life	TIAA-CREF	TIAA-CREF	TIAA-CREF	AIG Companies	TIAA-CREF	AIG Companies	Prudential Annuities	Lincoln Financial Group	Lincoln Financial Group	Lincoln Financial Group	TIAA	Brighthouse Financial	TIAA
5	Lincoln Financial Group	Lincoln Financial Group	Lincoln Financial Group	Lincoln Financial Group	Lincoln Financial Group	Prudential Annuities	Transamerica	AXA US	AIG Companies	AIG Companies	Prudential Annuities	Prudential Annuities	Brighthouse Financial	AIG Companies	Brighthouse Financial
6	Prudential Annuities	AXA Equitable	AIG Companies	AIG Companies	AXA Equitable	MetLife	Prudential Annuities	Prudential Annuities	Lincoln Financial Group	Prudential Annuities	AIG Companies	AIG Companies	AIG Companies	Nationwide	Allianz Life of North America
7	John Hancock	ING	AXA Equitable	Nationwide Financial	AIG Companies	AXA US	AXA US	Transamerica	Nationwide	Nationwide	Nationwide	Brighthouse Financial	Prudential Annuities	TIAA	Corebridge Financial
8	AIG	RiverSource Life Insurance	RiverSource Life Insurance	AXA Equitable	Transamerica	Transamerica	MetLife	MetLife	RiverSource Life Insurance	RiverSource Life Insurance	Brighthouse Financial	Nationwide	Allianz Life of North America	Allianz Life of North America	Prudential Annuities
9	Hartford Life	John Hancock	Nationwide Financial	RiverSource Life Insurance	RiverSource Life Insurance	Nationwide Life	Nationwide	Nationwide	Transamerica	New York Life	RiverSource Life Insurance	RiverSource Life Insurance	RiverSource Life Insurance	Prudential Annuities	Nationwide
10	Pacific Life	AIG	ING	AEGON USA	Nationwide Financial	RiverSource Life Insurance	RiverSource Life Insurance	RiverSource Life Insurance	MetLife	Transamerica	Pacific Life	Allianz Life of North America	Nationwide	RiverSource Life Insurance	New York Life
11	RiverSource Life Insurance	Nationwide Life	AEGON USA	Allianz Life of North America	Pacific Life	Pacific Life	Pacific Life	Pacific Life	Thrivent Financial for Lutherans	Pacific Life	Transamerica	Transamerica	New York Life	Pacific Life	RiverSource Life Insurance
12	Jackson National Life	Pacific Life	Sun Life Financial	Pacific Life	Allianz Life of North America	Thrivent Financial for Lutherans	New York Life	New York Life	New York Life	Thrivent Financial for Lutherans	New York Life	New York Life	Pacific Life	New York Life	Pacific Life
13	Nationwide Life	AEGON USA	Allianz Life of North America	Sun Life Financial	Thrivent Financial for Lutherans	New York Life	Thrivent Financial	Thrivent Financial for Lutherans	Pacific Life	Allianz Life of North America	Thrivent Financial for Lutherans	Pacific Life	Transamerica	Thrivent Financial for Lutherans	Thrivent Financial for Lutherans
14	AEGON USA	Sun Life Financial	Pacific Life	Protective Life	Protective Life	Allianz Life of North America	Ohio National	Allianz Life of North America	Allianz Life of North America	Fidelity Investments Life	Allianz Life of North America	Thrivent Financial for Lutherans	Thrivent Financial for Lutherans	Fidelity Investments Life	CMFG Life Insurance Company
15	Allianz Life	Hartford Life	John Hancock	New York Life	New York Life	Ohio National Life Insurance	Allianz Life of North America	Fidelity Investments Life	Fidelity Investments Life	Brighthouse Financial	Fidelity Investments Life	Fidelity Investments Life	Fidelity Investments Life	CMFG Life Insurance Company	Fidelity Investments Life
16	Fidelity Investments Life	Allianz Life	Thrivent Financial for Lutherans	Thrivent Financial for Lutherans	Fidelity Investments Life	Fidelity Investments Life	Fidelity Investments Life	Ohio National Life	Ohio National Life	Northwestern Mutual Life	Northwestern Mutual Life	Northwestern Mutual Life	CMFG Life Insurance Company	Transamerica	Massachusetts Mutual Life
17	Genworth Financial	Thrivent Financial for Lutherans	New York Life	John Hancock	Guardian Life of America	Protective Life	Northwestern Mutual Life	Northwestern Mutual Life	Northwestern Mutual Life	Ohio National Life	Great-West Financial	CMFG Life Insurance Company	Northwestern Mutual Life	Northwestern Mutual Life	Athene Annuity & Life
18	Sun Life Financial	Fidelity Investments Life	Protective Life	Fidelity Investments Life	Northwestern Mutual Life	Northwestern Mutual Life	Forethought Annuity	Forethought Annuity	Principal Financial Group	CMFG Life Insurance Company	CMFG Life Insurance Company	Principal Financial Group	Principal Financial Group	Protective Life	Northwestern Mutual Life
19	New York Life	New York Life	Fidelity Investments Life	Northwestern Mutual Life	Principal Financial Group	Principal Financial Group	Principal Financial Group	Protective Life	Massachusetts Mutual Life	Massachusetts Mutual Life	Massachusetts Mutual Life	Massachusetts Mutual Life	Massachusetts Mutual Life	Massachusetts Mutual Life*	Protective Life
20	Massachusetts Mutual Life	Massachusetts Mutual Life	Hartford Life	Guardian Life of America	Hartford Life	Massachusetts Mutual Life	Massachusetts Mutual Life	Massachusetts Mutual Life	CMFG Life Insurance Company	Principal Financial Group	Principal Financial Group	Securian Financial	Horace Mann Life	Athene Annuity & Life	Transamerica

Table E5: Top 20 ranking: individual fixed annuity sales

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	AIG	New York Life	Allianz Life of North America	AIG Companies	Allianz Life of North America	New York Life	Allianz Life of North America	Allianz Life of North America	Allianz Life of North America	New York Life	AIG Companies	AIG Companies	New York Life	AIG Companies	Athene Annuity & Life
2	New York Life	AIG	New York Life	Allianz Life of North America	New York Life	Allianz Life of North America	New York Life	New York Life	New York Life	AIG Companies	New York Life	New York Life	AIG Companies	Massachusetts Mutual Life	New York Life
3	Aviva	MetLife	AIG Companies	New York Life	AVIVA	Security Benefit Life	AIG Companies	AIG Companies	AIG Companies	Allianz Life of North America	Allianz Life of North America	Allianz Life of North America	Sammons Financial Companies	New York Life	Massachusetts Mutual Life
4	MetLife	Allianz Life	AVIVA	American Equity Investment Life	American Equity Investment Life	AIG Companies	Security Benefit Life	American Equity Investment Life	American Equity Investment Life	Global Atlantic Financial Group	Global Atlantic Financial Group	Global Atlantic Financial Group	Athene Annuity & Life Co.	Athene Annuity & Life	Corebridge Financial
5	AEGON USA	AVIVA	American Equity Investment Life	AVIVA	Security Benefit Life	American Equity Investment Life	American Equity Investment Life	Forethought Annuity	Athene Annuity & Life	Athene Annuity & Life	Athene Annuity & Life	Athene Annuity & Life	Global Atlantic Financial Group	Global Atlantic Financial Group	Global Atlantic Financial Group
6	Allianz Life	AEGON USA	Lincoln Financial Group	Lincoln Financial Group	AIG Companies	Great American	Forethought Annuity	Symetra Financial	Global Atlantic Financial Group	Nationwide	Pacific Life	Pacific Life	Massachusetts Mutual Life	Allianz Life of North America	Sammons Financial Companies
7	Jackson National Life	Lincoln Financial Group	Jackson National Life	Great American	Lincoln Financial Group	Pacific Life	Great American	Great American	Midland National	Great American	Nationwide	Nationwide	Allianz Life of North America	Fidelity & Guaranty Life	Fidelity & Guaranty Life
8	Allstate Financial	Jackson National Life	MetLife	MetLife	Great American	Massachusetts Mutual Life	Symetra Financial	Nationwide	Great American	American Equity Investment Life	Great American	Lincoln Financial Group	Fidelity & Guaranty Life	American Equity Investment Life	Allianz Life of North America
9	Principal Life	Pacific Life	ING	Jackson National Life	Jackson National Life	EquiTrust Life	MetLife	Lincoln Financial Group	Symetra Financial	Pacific Life	Massachusetts Mutual Life	Massachusetts Mutual Life	Security Benefit Life	Sammons Financial Companies	Pacific Life
10	Hartford Life	RiverSource Life Insurance	Great American	North American Company for Life and Health	Pacific Life	Symetra Financial	Pacific Life	MetLife	Pacific Life	Symetra Financial	American Equity Investment Life	American Equity Investment Life	American Equity Investment Life	Symetra Financial	Western Southern Group
11	Western Southern Group	American Equity Investment Life	Symetra Financial	Symetra Financial	Midland National	Midland National	Fidelity & Guaranty Life	Midland National	MetLife	Security Benefit Life	Symetra Financial	Jackson National Life	Great American	Security Benefit Life	USAA Life
12	Lincoln Financial Group	ING	Midland National	Midland National	Nationwide Financial	Jackson National Life	Athene Annuity & Life	Pacific Life	Security Benefit Life	Brighthouse Financial	Principal Financial Group	Great American	Nationwide	Western Southern Group	Nationwide
13	ING	John Hancock	North American Company for Life and Health	Pacific Life	MetLife	Lincoln Financial Group	Lincoln Financial Group	Athene Annuity & Life	Nationwide	Midland National	Lincoln Financial Group	Fidelity & Guaranty Life	Pacific Life	USAA Life	Symetra Financial
14	Genworth Financial	Symetra Financial	Prudential Annuities	American National Life	Fidelity & Guaranty Life	AVIVA	EquiTrust Life	Principal Financial Group	North American Company for LH	Fidelity & Guaranty Life	Fidelity & Guaranty Life	Symetra Financial	Western Southern Group	Nationwide	Security Benefit Life
15	American Equity Investment Life	Western Southern Group	Western Southern Group	ING	EquiTrust Life	Genworth Financial	Midland National	Fidelity & Guaranty Life	Principal Financial Group	Principal Financial Group	Delaware Life	Principal Financial Group	Symetra Financial	Pacific Life	Brighthouse Financial
16	Protective Life	American National Life	Pacific Life	USAA Life	Massachusetts Mutual Life	MetLife	Genworth Financial	Security Benefit Life	Fidelity & Guaranty Life	Massachusetts Mutual Life	Western Southern Group	Western Southern Group	Delaware Life	Delaware Life	Lincoln Financial Group
17	Midland National	Allstate Financial	USAA Life	Western Southern Group	Symetra Financial	Berkshire Hathaway	Voya Financial	North American Company for Life and Health	Lincoln Financial Group	North American Company for Life and Health	Midland National	Security Benefit Life	Brighthouse Financial	Great American*	American Equity Investment Life
18	Old Mutual Financial Network	USAA Life	American National Life	Genworth Financial	Genworth Financial	ING	Massachusetts Mutual Life	EquiTrust Life	Massachusetts Mutual Life	Lincoln Financial Group	North American Company for LH	Delaware Life	Protective Life	American National	Delaware Life
19	RiverSource Life Insurance	Midland National	John Hancock	Security Benefit Life	North American Company for L&H	North American Company for L&H	Berkshire Hathaway	Voya Financial	Voya Financial	Delaware Life	Reliance Standard Life	Midland National	EquiTrust Life	EquiTrust Life	EquiTrust Life
20	John Hancock	Hartford Life	National Life Group	Massachusetts Mutual Life	ING	Fidelity & Guaranty Life	Jackson National Life	Western Southern Group	Western Southern Group	American National	Protective Life	North American Company for L&H	USAA Life	National Life Group	National Life Group

E3 Panel data from NAIC

We present firm panel data provided by the NAIC. We exploit the detailed firm level datasets related to the annuity line of business consigned in the annual financial statements. Specifically, we use the Analysis of operations by line of business schedule for the 2019–2022 period and the Analysis of annuity operations by line of business schedule for the 2010–2018 period, to collect information about Net Premiums for annuity contracts, Net investment income, Miscellaneous Income which is the sum of the following three elements: i) Income from fees associated with investment management, administration and contract guarantees from Separate Accounts, ii) Charges and fees for deposit-type contracts, and iii) Aggregate write-ins for miscellaneous income. The Miscellaneous Income is an additional source of revenues for the insurance company and contains fees charged to annuitants. We also collect Total payments including essentially annuity benefits, surrender benefits and withdrawals for life contracts, and payments on supplementary contracts with life contingencies. We gathered also insurance related expenses including commissions, general insurance expenses, insurance taxes, and net transfers to or from Separate Accounts. Net gain from operations before dividends to policyholders is collected as a proxy for operating profitability. More importantly, this dataset is given by annuity type: variable annuities, fixed annuities, and indexed annuities.

The following table indicates summary statistics for the gathered variables for our firm level panel during the period 2010-2022. Statistics are given for variable and fixed annuities separately.

Table E6: Summary statistics NAIC data (in $ million)

	Variable annuity				Fixed annuity			
Variable	Obs	Mean	Median	SD	Obs	Mean	Median	SD
Annuity premiums	1,539	1,441.804	75.998	3,247.401	4.438	234.713	6.835	983.883
Net Investment income	1,539	158.185	6.803	790.753	4.438	114.705	8.281	341.080
Charged fees	1,539	258.754	17.444	637.299	4.438	7.550	0.000	47.995
Total payments	1,539	1,607.621	148.130	3,322.595	4.438	317.442	15.598	1,060.648
Expenses	1,539	43.504	-4.866	2,044.924	4.438	14.777	1.039	584.467
Net gain from operations before dividends	1,539	162.550	6.301	620.768	4.438	25.661	0.733	171.088