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

Preliminary

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Abstract

We investigate the causes of the gap in mergers and acquisitions (M&A) 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 in the life insurance sector declined after 2012. We find evidence that low interest rates observed during the implementation of the quantitative easing policy of the Fed 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, quantitative easing policy, life insurance annuity, variable annuity.

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 resource allocation and welfare of different 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 targets profitability and mergers and acquisitions. A significant decrease in mergers and acquisitions (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 U.S. life and nonlife insurance sectors, using the difference-in-differences (DID) methodology.

Our DID 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 reason for this decline in the life insurance sector is the decline of sales, particularly in the variable annuity business. We find evidence that the low interest rates observed during the implementation of the quantitative easing (QE) policy of the Fed from

2008 to 2012 caused the difference by reducing M&As in the life insurance sector after 2012.[1]

After the financial crisis of 2007-2008, the US monetary authorities made a major shift in 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 important drops were observed in the QE2 and QE3 phases. In 2012, a plan to increase long-maturity Treasury securities holdings at $45 billion per month was implemented. As a result, life insurance products became less attractive to investors, leading to a decline in sales after 2012. In addition, many insurers stopped offering minimum return guarantees in response to falling interest rates because this policy became very expensive. This also 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 triggered by high premiums charged to policyholders, amplified by 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. Section 2 analyzes the main characteristics of the US insurance market during the 1990-2022 period in the insurance industry. Section 3 presents the evolution of M&A in the US insurance market from 1990 to 2022, while

[1] The three phases of the QE were: 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 additional time.

Section 4 is devoted to the parallel trend analysis. We then discuss the DID analysis in Section 5 and the causes of the 2012 shock in the life insurance sector in Section 6. Section 7 concludes the paper.

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) or to reduce their riskiness and/or 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 failure probability resulting from combinations of two property-casualty firms is lower than that resulting 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. However, 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 bidders' firm value could be observed. 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. 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&A. 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 the 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.

2. The US insurance market

The insurance industry comprises three main sectors. The first sector is property and casualty insurance. 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 annuity contracts). This sector collects a higher volume of premiums than the other two. In our analysis, we consider target insurers with SIC code 6331 as insurers corresponding to the property and casualty (P&C) market.[2] Target insurers with SIC codes 6321 and 6324 are considered insurers corresponding to the health insurance market (Accident and health insurance and Hospital and Medical Service Plans). Target insurers with SIC code 6311 correspond to the Life Insurance market (Life).

We divide the three insurance sectors into two main 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 analysis, 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 summarizes the division of insurance sectors.

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

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

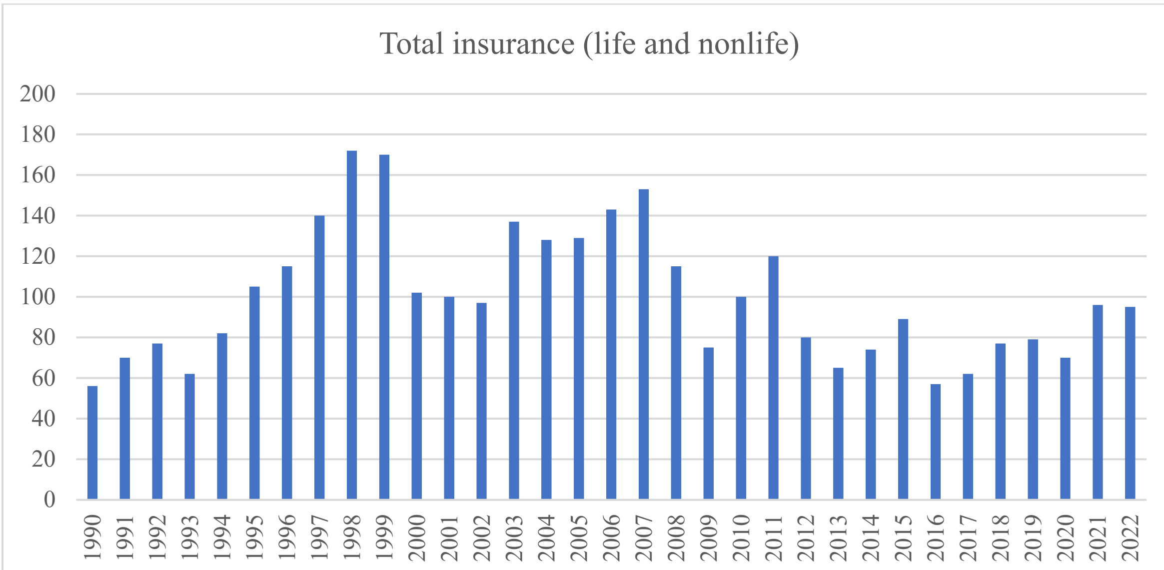
Nonlife insurance			Life and annuities insurance
Property damage and miscellaneous risks	Civil liability	Health insurance	Life insurance
Coverage for movable and immovable property belonging to the insured	Cover for damage of any kind caused by the insured to third parties	Coverage for medical services to the insured	Guarantees in the event of the insured's life or death
Sector: Distribution of nonlife insurance compensation Insurers with SIC codes 6321, 6324, 6331, 6351, 6361, and 6399.			Sector: Life insurance Lump-sum capitalization 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 of the US insurance industry during the period of analysis. The record years of 1998 and 1999 have not been broken since then. In fact, this period corresponds to the internet and new technologies growth of the years 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.

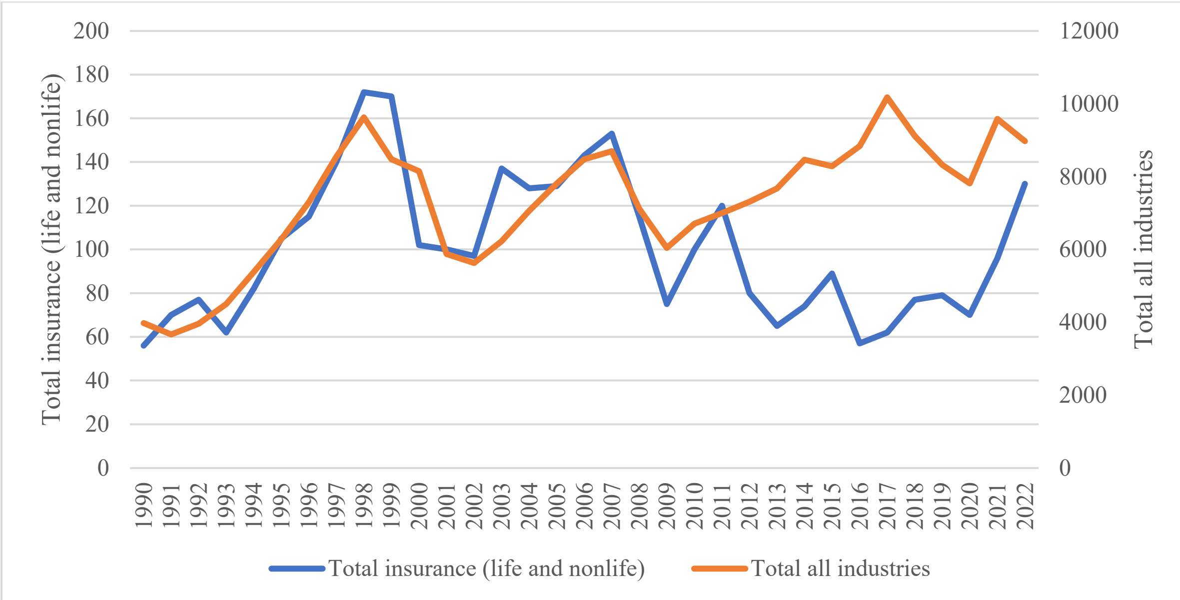
Figure 1: Histogram of the annual number of M&A transactions
related to US target insurers, 1990-2022



Data source: SDC database.

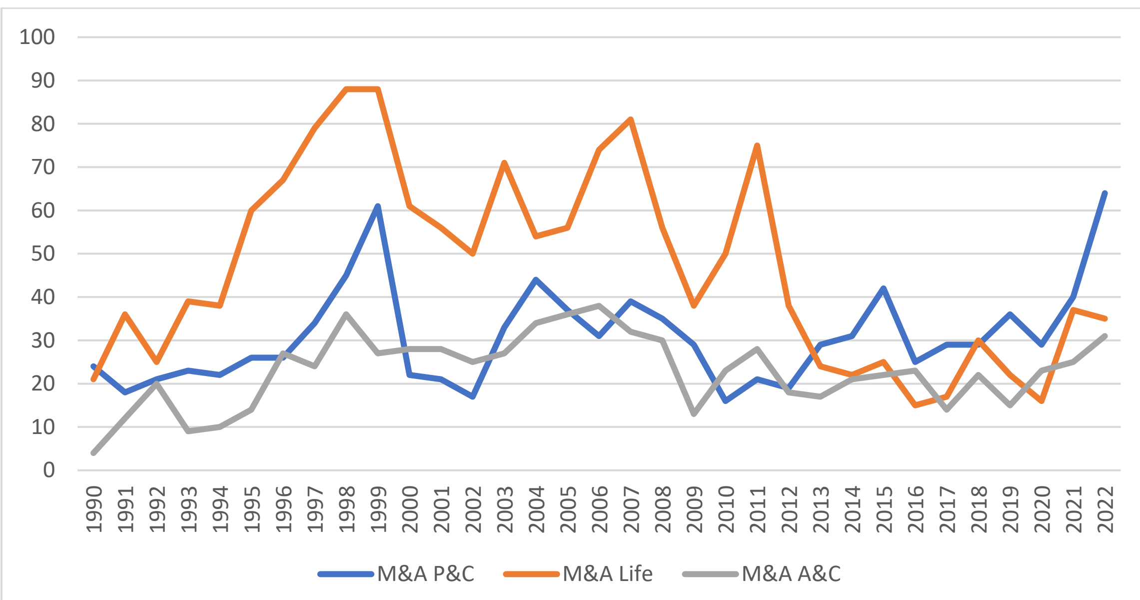
Figure 2 depicts three peaks of M&As across all industries in the US (1998, 2007, and 2017) during the same period. As documented above, only two waves of M&As occurred in the US insurance industry during that period. Since the 2007 peak, the M&A market has exhibited an overall downward trend throughout 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-2009 period is marked by a shift behavior of insurers across the US insurance industry.

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: MA trends of target insurers by the three insurance sectors in the US, 1990-2022



Data source: SDC database.

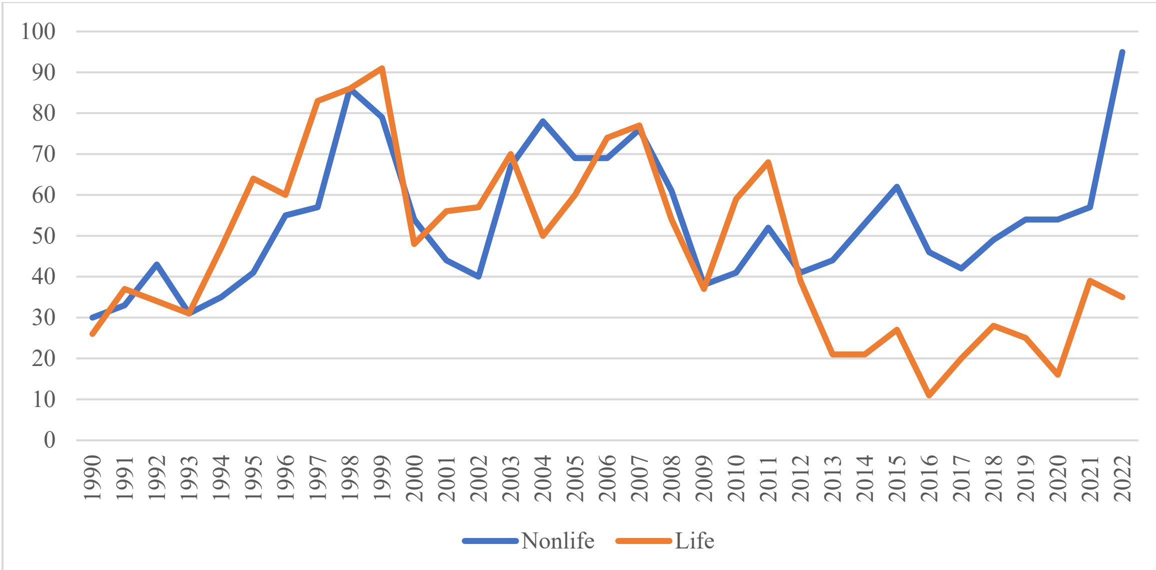
Table 2: Annual mean and standard deviation of the M&A in each sector

	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

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 than with life insurers. We also observe the 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 that includes property and casualty insurance and health insurance. Given that the two main lines of insurance can be affected differently by climate risk, market conditions, and insurance regulation, 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 mergers and acquisitions 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 retain the years 2009 and 2012 as potential candidates for a treatment date in our analysis with the difference-in-differences (DID) method. The choice of the treatment date for our DID method thus seems ambiguous. We will 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. Therefore, we plan to define our treatment effect as a negative 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 data of M&As in the two insurance sectors (Berck et al., 2016; 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 nonlife insurance sector versus the number of M&As of target insurers in the life insurance sector 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 nonlife insurance sector and the number of target insurer M&As in the life 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, the median statistical test, the distribution statistical test, the monotonicity test, 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 3, where the differences between various statistics are presented. Our 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 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 average number of M&As in the nonlife sector and the average number of M&As in the life sector are statistically different (Student's test) 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 Table 3, the three tests cannot discriminate between the two dates. Appendix C presents more details.

Table 3: Statistical descriptions (median, mean of the number of M&As) and validation tests of the treatment date

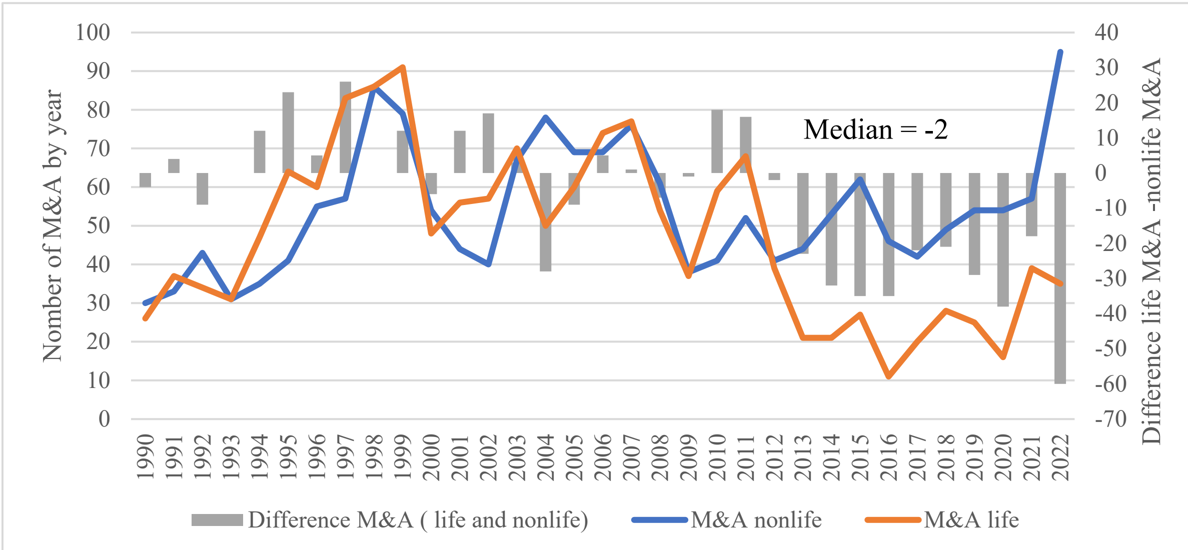
Period	1990-2009	Post-2009	1990-2012	Post-2012	1990-2022
Median	2	-23	3	-30.5	-2
Mean	2.8	-21.6154	3.8261	-31.3	-6.818
Student's test	1.015	-3.593	1.499	-8.111	-1.926
Median test	0.48	0.023	0.383	0.002	0.473
Wilcoxon test	1.028	-2.797	1.446	-2.805	-1.555

4.1.2. Monotonicity hypothesis

We employ an additional criterion called the monotonicity hypothesis, often used in the literature to evaluate the treatment effect. This hypothesis postulates that when there is a change, the treatment effect can go in only 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 with 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 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 observed for each year of the post-2012 period (11 years with a negative difference versus 0 year 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. In 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. To conclude, 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 3). This criterion 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. 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 create a dummy variable $\mathrm{Treated_L}$ equal to one for the treated group. We also 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 $\mathrm{Treated_L} \times \mathrm{Year}$ 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 4 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 $\mathrm{Treated_L} \times \mathrm{Year}$ interaction variables prior to 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%. In 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 retained for our DID method.

Table 4: 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
$Treated_L$×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

	Parallel trends		Validation tests			
Independent variable	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
$Treated_L$×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	

Notes: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

To ensure the reliability of our validation test of the choice of treatment date for our DID method, we conduct two robustness tests. The first test 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 confirm the validation of the year 2012 as the treatment date to retain for our DID method.

5. DID analysis

5.1. Variable description

5.1.1. Introduction

To isolate a causal effect related to the separation observed in 2012, we have opted for a natural experiment method using the difference-in-differences (DID) estimator. This estimator 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.

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 $\mathrm{Treated}_{\mathrm{L}}$ 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, $\mathrm{Treated}_{\mathrm{L}}$ and $\mathrm{Post2012}$, in order to assess the impact of the treatment on the units in our treatment group. Our interaction variable $\mathrm{Treated}_{\mathrm{L}}\times\mathrm{Post2012}$ enables us to capture the effect of the treatment administered to the units in the treatment group.

Table 5 provides a detailed description of the explanatory variables introduced into our model (1), together with their construction method. The goal is to empirically verify the difference between M&As in the life and nonlife insurance sectors in the US using the DID method.

Table 5: Description of explanatory variables

Explanatory variable	Construction method
$\mathrm{Treated}_{\mathrm{L}}$ (dichotomous)	$\mathrm{Treated}_{\mathrm{L}}$ 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 that takes the value 0 if the period is before the treatment and the value 1 if the period is after the treatment.
$\mathrm{Treated}_{\mathrm{L}}\times\mathrm{Post2012}$ (dichotomous)	$\mathrm{Treated}_{\mathrm{L}}\times\mathrm{Post2012}$ 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 a 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 $\mathrm{Treated}_{\mathrm{L}} \times \mathrm{Post2012}$ on the number of M&A targets per State and per year.

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

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

where:

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

$\mathrm{Treated}_{\mathrm{L}} \times \mathrm{Post2012} = 1$ 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 effects that occur in a given State i on a given date *t*.

5.2. Results

The results presented in Table 6 indicate that the coefficient of our variable $\mathrm{Treated}_{\mathrm{L}} \times \mathrm{Post2012}$ is negative and statistically significant at 1% in the basic model. This suggests a downward effect on the number of M&As in the treated group in the post-2012 period.

Table 6: 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
$Treated_L \times Post2012$ (2012 = 0)	-0.689***	-0.689***	-0.689***
	(0.127)	(0.127)	(0.126)
Number of events		0.002	
		(0.011)	
Insured losses			-1.27e-11
			(3.16e-11)
Constant	1.093***	1.086***	1.099***
	(0.015)	(0.041)	(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

Notes: *** p<0.01. Standard errors were computed with the bootstrapping method clustered at the State level.

Table 6 also shows that climate risk events have no effect on the DID analysis. These events are from Verisk database, that documents all climate risk events of 25M$ or more for total insured property losses. Number of events is the total numbers per year and insured losses are the total losses of the insurance industry per year (Dionne et al., 2023).

Table 7 presents an additional test for the consideration of climate risk events (Kranz, 2022). The test permits to take into account of time varying covariates. Note that the first regression in Panel A omits observations in the treatment group. The regression in Panel B uses the results of Panel A estimation. The estimated effect of a given climate risk variable on the number of M&A per year is subtracted from the dependent variable in Panel B. We observe in Panel B that the results remain stable when compared to those of Table 6.

Table 7: 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&A per year for the nonlife sector			
Dependent variable	Number of M&A per year and per State in the nonlife sector		
Independent variable			
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			
Independent variable	Climate events	Insured climate losses	Log transformation of climates insured losses
$Treated_L \times Post2012$	-0.689***	-0.689***	-0.689***
	(0.134)	(0.134)	(0.131)
Constant	0.4728***	0.5472***	0.4959***
	(0.028)	(0.028)	(0.028)
Observations	3,366	3,366	3,366
R-squared	0.5387	0.5447	0.5458

Notes: *** 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.

5.3. Robustness analysis[3]

We now investigate whether our conclusions are robust to alternative econometric causal methodologies. The standard DID relies on the parallel trends assumption suggesting that,

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

in the absence of the treatment, both groups would have experienced the same outcome trends. However, recent studies unveiled that the standard parallel trends methodology may be a questionable modelling assumption and that pre-trends tests may come with caveats (Kahn-Lang and Lang, 2020). We then use recent and more flexible econometric approaches that rely less on the parallel trend 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 a manner that this synthetic control is as closely matched as possible to the treated units in pre-treatment outcomes. Unlike the classical DID framework where control units are equally weighted, the SC approach reweights control units and relaxes the need for the parallel trend 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 which can be applied in panel datasets and aims to link the standard DID and the SC methods to 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 help relaxing the parallel trend assumption.

Besides the weighting scheme for control units, as in the SC method, the SDID 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 8 reports the results for the two additional methods where we do not aggregate any more the MA in the Health and the P&C sectors. 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 equal weights. These robustness tests show that the standard DID estimation of Table 6 remains in the range of the different coefficients we find with different and more flexible econometric methodologies. We also observe that the SDID and the DID estimations for the treatment effect are more stable than the estimation by the SC method. It seems that the SC method performs less with long panels.

Table 8: 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			
$Treated_L \times Post2012$	-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			
$Treated_L \times Post2012$	-0.680***	-0.651***	-0.614***
	(0.112)	(0.135)	(0.166)

Observations (State-Year)	5,049	5,049	5,049

Notes: *** p<0.01. Each regression includes fixed effects for State and time. Standard errors were computed from the bootstrapping method clustered at the State level.

6. Origin of the 2012 shock in the life insurance market (preliminary)

6.1. Interest rate policy and decline in life insurers' sales in the post-2012 period

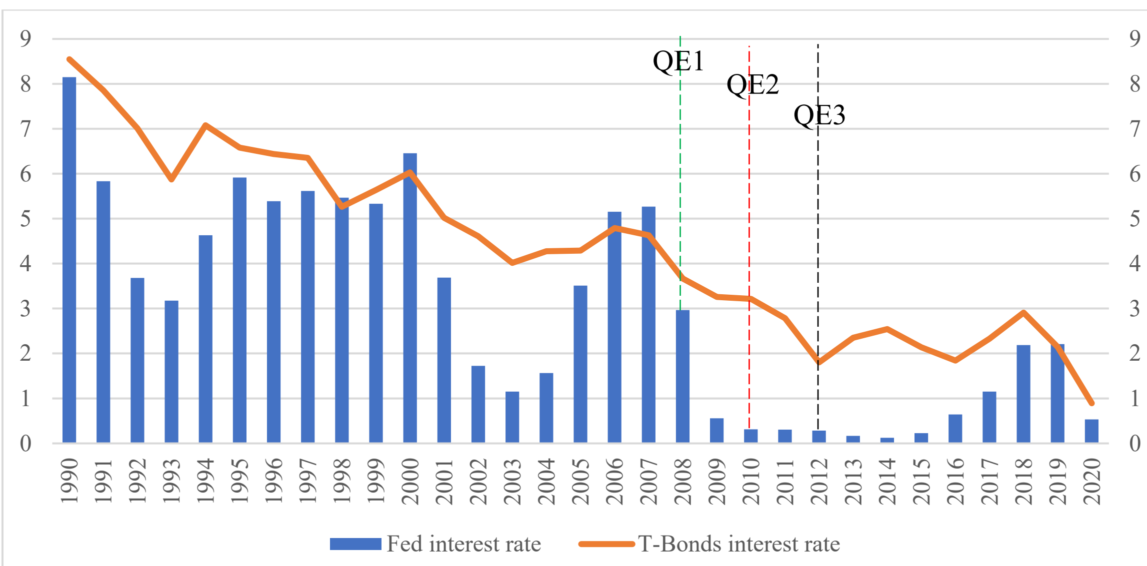
Following the financial crisis of 2007-2008, the US monetary authorities made a major shift in their monetary policy. This change in monetary policy involved the purchase of large-scale assets in order to inject liquidity into the economy through quantitative easing (QE) policies. Specifically, the Fed 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 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 Treasured securities holding at $45 billion per month. By implementing a policy of quantitative easing, the Fed demonstrated its determination to keep its key rates low enough, for long enough. Figure 6 clearly illustrates the impact on interest rates of the three major quantitative easing measures implemented in the United States after the 2007-2008 financial crisis.[4] Finally, in 2012, the Fed implemented an operation twist mechanism by

[4] On the effects of QE, 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.

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 its key interest rates low enough for long enough. If markets found this commitment credible, they would anticipate low short-term interest rates. Long-term interest rates would then 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 $1.725 trillion program of purchasing long securities between the end of 2008 and March 2010 would have caused long-term rates to fall by around 50 basis points. Figure 6 supports the idea that quantitative easing measures could cause long-term interest rates to decline.

Figure 6: Trends in the Fed's key interest rate and 10-year T-bond interest rate in the United States, 1990-2020



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 the guarantee on the minimum interest rate on 10-year T-bonds often used to calculate the value of variable annuities in the US (Berends et al., 2013). Indeed, annuity contracts include a guarantee on the minimum interest rate used to calculate their value.[5] 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 rate falls below 3%, as was the case between 2012 and 2020, the insured continued 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. Tables 9 and 10 present the effect of interest rate on annuities sales. We observe a large significant effect of the Fed interest rate on the variable annuity market after 2012 in Table 9 and a similar effect of the T-bond interest rate in Table 10.

Table 9: Effect of interest rate on annuity sales, 2000-2018

Dependent variable	Variable annuity ($ billion)	Fixed annuity ($ billion)	Total annuity ($ billion)
Post2012	-122.7***	24.99	0.875
	(16.82)	(64.99)	(1.917)
Fed interest rate	6.788***	-2.445*	-0.155
	(1.928)	(1.386)	(0.101)
Post2012×Fed interest rate	-15.12**	7.990	0.211
	(5.343)	(5.781)	(0.160)
Fee charged share	1.208	8.253	0.158*
	(2.202)	(8.210)	(0.0831)
Post2012×Fee charged share	6.458***	-4.498	-0.0823
	(1.376)	(8.851)	(0.0907)
Life expectancy	21.78	-21.16	-0.350

[5] 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 degails.

	(13.58)	(15.16)	(0.573)
GDP growth rate	1.803	-4.207**	-0.150*
	(1.783)	(1.778)	(0.0762)
Constant	-1.583	1.701	29.70
	(1.045)	(1.137)	(43.69)
State fixed effect	Y	Y	Y
Double SE clustering	State/Year	State/Year	State/Year
Observations	969	969	969
R-squared	0.854	0.791	0.947

Notes: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in Appendix F.

Table 10: Effect of T-bonds yield rate on annuity sales, 2000-2018

Dependent variable	Variable annuity ($ billion)	Fixed annuity ($ billion)	Total annuity ($ billion)
Post2012	-85.88**	48.97	-2.118
	(37.98)	(63.18)	(1.917)
T-bonds yield rate	17.69***	1.508	-0.417
	(5.081)	(5.995)	(0.291)
Post2012×T-bonds yield rate	-20.19**	9.935	0.833*
	(8.579)	(8.647)	(0.406)
Fee charged share	4.939**	15.17**	0.0952
	(1.854)	(7.186)	(0.0743)
Post2012×Fee charged share	6.478***	-10.71	-0.0276
	(1.986)	(7.588)	(0.0962)
Life expectancy	15.64	-30.35**	-0.225
	(14.62)	(13.42)	(0.537)
GDP growth rate	0.302	-3.656*	-0.149*
	(2.117)	(1.782)	(0.0784)
Constant	-1.190	2.366**	22.18
	(1.140)	(1.013)	(41.65)
State fixed effect	Y	Y	Y
Double SE clustering	State/Year	State/Year	State/Year
Observations	969	969	969
R-squared	0.841	0.775	0.947

Notes: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in Appendix F.

In other words, the interest rate factor seems to explain the drop in variable annuity sales and therefore the decline in total life insurance business during the post-2012 period. In reality, the interest rate factor may have had a dual effect on the decline in sales in the post-2012 period. First, the low interest rates observed after 2012 may have exerted upward pressure on the prices of life insurance products (negative relationship between interest rates and prices). This would have reduced sales. Second, it is also possible that the interest rate differential (interest rate and guaranteed 3% return), representing interest rate risk management costs assumed by life insurers during the post-2012 period, may have exerted upward pressure on variable annuity product prices. This would have led to lower sales. The observed coefficients are positive in the two tables, however.

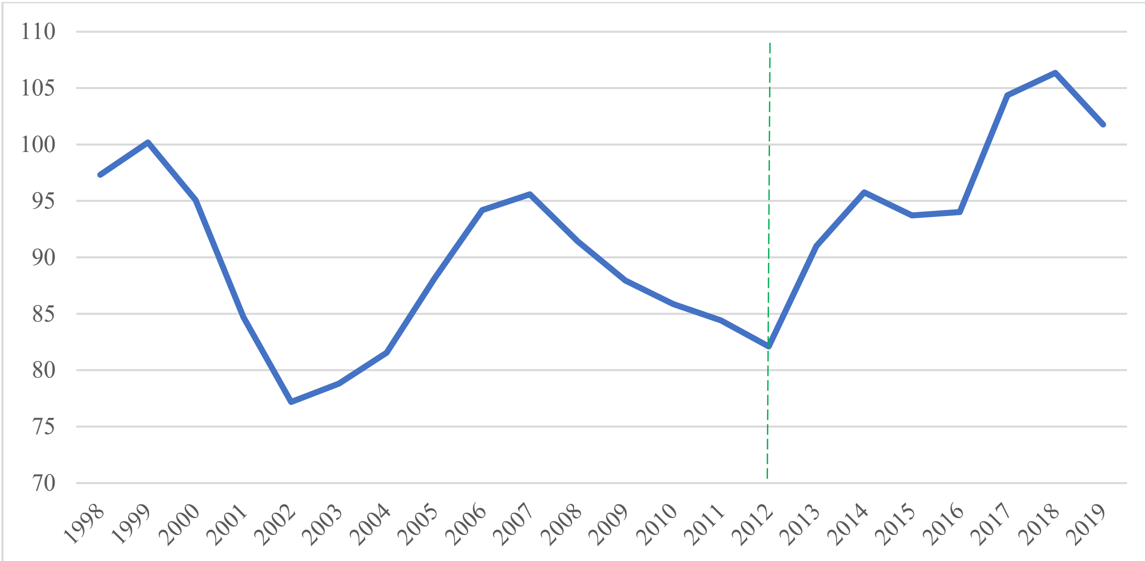
6.2. Combined ratio

We propose that the economic difficulties in the life insurance sector (annuity and life business) observed in the post-2012 period could have been a cause of the difference in the number of M&As of target insurers in the nonlife insurance sector, relative to the number of M&As of target insurers in the life insurance sector. The change in interest risk management in the life insurance industry during the post-2012 period could have been the cause of the difference. The new monetary policy motivated by the 2007-2009 financial crisis could have been the roots of the economic difficulties in the life insurance sector. Indeed, the very low interest rates may have significantly affected the investment benefits in annuities in the life insurance industry during the period of analysis. Looking at these potential causes, it appears that different events occurred in the years preceding 2013 might have caused an exogenous change in the treated units that increased the difference in the number of M&As of the treatment group relative to the control group.

We consider that M&A transactions are positively correlated with the performance of the insurance business. The better the insurance business performs, the more M&As should occur in the insurance industry. One of the best indicators of insurer performance is the combined ratio. It consists of the ratio of premiums paid (claims paid + operating expenses) to premiums collected (insurance policies sold). This indicator determines whether premiums collected are sufficient to cover claims paid and operating expenses. Clearly, the most obvious risk for insurers is that premiums collected (sales) are insufficient to pay policyholders' claims. 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 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, different components of the 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. Two explanations may correspond to this rise in the combined ratio observed during the post-2012 period. First, claims costs may have grown faster than 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 paid claims effectively.

Figure 7: Trend in the combined ratio for the US life insurance sector



Source: NAIC. Formula 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 LIMRA (Life Insurance Marketing and Research Association) 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 can conclude that the life insurance market as a whole experienced a downturn after 2012 due to the high costs of products sold.

The formula for calculating the combined ratio suggests that the combined ratio is an increasing function of the variables claims costs and management expenses, and a decreasing function of the premiums collected. The more claims paid increase, the more the combined ratio increases, and the more premiums collected decrease, the more the combined ratio also increases. The results in Table 11 confirm the positive influence of premiums collected after 2012 in the variable annuity business line on the combined ratio and the positive influence of payments after 2012 on the combined ratio. The variable Payments after 2012 is negatively significant for life business line and fixed annuity line, however. The results clearly show that the negative shock in premiums collected (sales) drove the combined ratio in the life insurance sector upward during the post-2012 period.

Table 11: Determinants of the combined ratio in the Life sector, 2000-2018

Dependent variable	Combined ratio Life sector		
	Life	Annuity business line	
Independent variable	business line	Variable	Fixed
Post2012	-90.70***	-70.24**	-27.34
	(28.58)	(25.69)	(27.32)
1/Premium ($ billion)	0.0585**	-1.072	740.4
	(0.0275)	(2.071)	(810.4)
Post2012× (1/Premium ($ billion))	-0.0793**	5.737**	2.526*
	(0.0336)	(2.073)	(1.369)
Payments ($ billion)	0.207*	0.172***	0.539***
	(0.115)	(0.0412)	(0.0766)
Post2012×Payments ($ billion)	-0.671**	0.265***	-0.261**
	(0.296)	(0.0422)	(0.0955)
Expenses ($ billion)	-0.241	-2.931*	-6.723**
	(1.057)	(1.447)	(2.959)
Post2012×Expenses ($ billion)	7.696***	-1.508	5.732
	(2.129)	(1.459)	(3.479)
Constant	67.81**	88.19***	56.18**
	(25.42)	(25.65)	(21.04)
State fixed effect	Y	Y	Y
Double SE clustering	State/Year	State/Year	State/Year
Observations	969	969	969
R-squared	0.689	0.903	0.912

Notes: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in Appendix F.

Table 12 indicates that, during the post-2012 period, the positive effect of variable annuity premium on mergers and acquisitions decreased while the fixed annuity premium had no significant effect. Table 13 presents a similar result regarding the effect of T-bonds yield rate.

Table 12: Effect of insurance activity on mergers and acquisitions in the life insurance industry

Variable	M&A Life
Post2012	-6.061* (3.159)
INSURANCE ACTIVITY	
Annuity business line	
Variable annuity premium ($billion)	0.0274*** (0.00425)
Post2012×Variable annuity premium ($billion)	-0.0115*** (0.00195)
Fixed annuity premium ($billion)	-0.00267 (0.00608)
Post2012×Fixed annuity premium ($billion)	-0.00492 (0.00669)
Annuity payments ($billion)	-0.0133*** (0.00393)
Post2012×Annuity payments ($billion)	0.00936*** (0.00204)
Expenses annuity ($billions)	-0.401*** (0.135)
Post2012×Expenses annuity ($billions)	0.403** (0.167)
Life business line	
Combined ratio Life business line (%)	-0.00249 (0.0151)
Post2012×Combined ratio Life business line	-0.0125 (0.0741)
INVESTMENT ACTIVITY	
Net investment ratio	0.0175

Variable	M&A Life
	(0.0207)
CONTROL VARIABLES	
Credit-risk-free interest rate	0.0976
	(0.0840)
GDP	0.000367***
	(0.000111)
Constant	0.256
	(0.538)
State fixed effect	Y
Double SE clustering	State/Year
Observations	969
R-squared	0.526

Notes: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in Appendix F.

Table 13: Effect of interest rate on mergers and acquisitions
in the life insurance industry

Variable	M&A Life
Post2012	-419.3***
	(90.80)
INSURANCE ACTIVITY	
Annuity business line	
T-bonds yield rate (%)	0.945
	(0.736)
Post2012×T-bonds yield rate	-1.268***
	(0.361)
Fees charged ($billion)	0.0238
	(0.281)
Post2012×Fees charged ($billion)	-0.337***
	(0.0749)
Life expectancy	-2.206***
	(0.649)
Post2012×Life expectancy	5.494***
	(1.228)
Annuity payments ($billion)	0.000729
	(0.0121)
Expenses annuity ($billions)	0.254

Variable	M&A Life
	(0.369)
Life business line	
Combined ratio Life business line (%)	-0.0229
	(0.0787)
Post2012×Combined ratio Life business line	-0.0448
	(0.0693)
INVESTMENT ACTIVITY	
Net investment ratio	0.0310
	(0.0967)
CONTROL VARIABLES	
Credit-risk-free interest rate	-0.456**
	(0.193)
GDP	0.000723
	(0.000480)
Constant	157.5***
	(46.29)
State fixed effect	Y
Double SE clustering	State/Year
Observations	969
R-squared	0.524

Notes: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in Appendix F.

6.3. Insurance business in the two sectors

6.3.1. Premiums to GDP

We have just demonstrated that it was the 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, which in turn may have dampened M&A transactions in life insurance. 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, and M&A transactions. The ratio of premiums collected (sales) to GDP is known as the penetration rate, and is often used by insurance professionals. It is an interesting indicator for assessing the importance of this business in a country's economy. It shows whether insurance business as a proportion of 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 overall GDP. Conversely, a drop in demand for insurance products translates into a lower penetration rate.

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

Our econometric results presented in Table 14 confirm the negative effect of life insurance business activity in the total life insurance sector, measured by Premium % of GDP, and in each business line on M&A transactions.[6] Specifically, insurance business can explain trends in M&A transactions in the United States. Thus, one could argue that the loss of the parallel M&A trend observed between our two sectors in the post-2012 period is driven by a loss of the parallel trend in the insurance business market.

Table 14: M&A and Premium to GDP ratio in the life sector

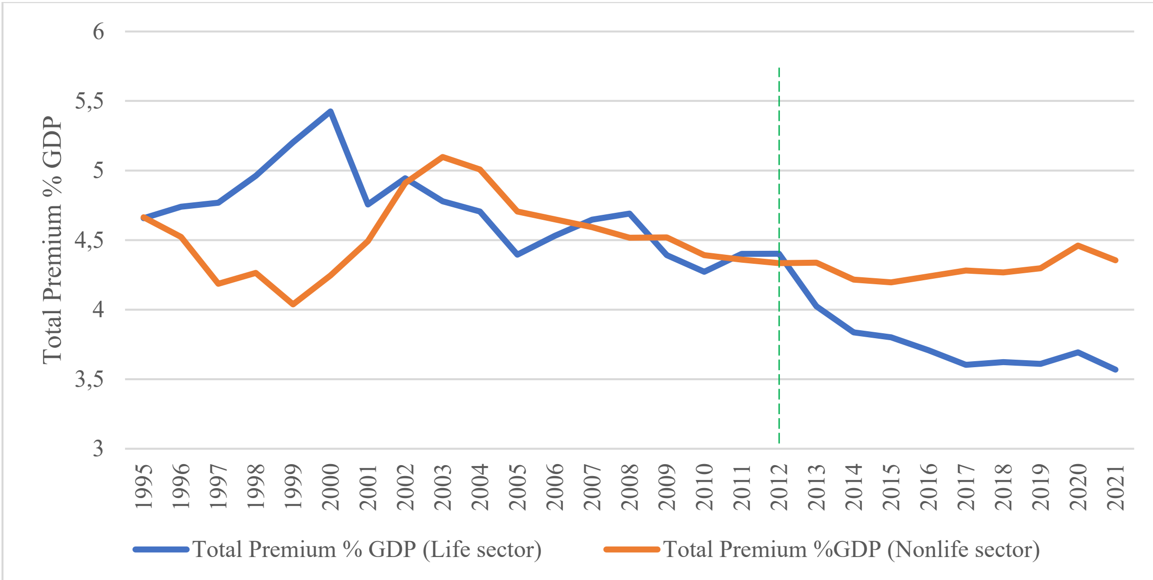
Dependent variable: M&A	Total life sector	Annuity business line	Life business line
Independent variable	Coefficient	Coefficient	Coefficient
Post2012	0.976	0.0978	1.195
	(2.242)	(1.719)	(1.587)
Premium % of GDP	14.70	10.84	32.28
	(9.041)	(8.939)	(36.06)
Post2012×Premium % of GDP	-14.31***	-24.69***	-39.01***
	(2.070)	(4.368)	(9.531)
Payments ($ billions)	0.00244	0.00791	0.0123*

[6] A non-significant link between nonlife insurance business activity after 2012 and M&A transactions was obtained. Details are available from the authors.

	(0.00161)	(0.00542)	(0.00684)
Post2012×Payments ($ billions)	0.00238	0.00113	-0.0116
	(0.00280)	(0.0163)	(0.0180)
Expenses ($ billion)	-0.0236	-0.00763	-0.0186
	(0.0396)	(0.0739)	(0.0809)
Post2012×Expenses ($ billion)	-0.0526	-0.00303	0.00464
	(0.0904)	(0.0745)	(0.0773)
Log total number of deaths	-0.389	-2.544	0.240
	(4.719)	(5.871)	(5.050)
GDP growth rate	0.0623*	0.0898*	0.0833**
	(0.0342)	(0.0447)	(0.0382)
Constant	5.875	37.31	-4.167
	(68.87)	(85.44)	(73.39)
State fixed effect	Y	Y	Y
Double SE Clustering	State/Year	State/Year	State/Year
Observations	969	969	969
R-squared	0.568	0.564	0.567

Notes: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. Variables are described in Appendix F.

Figure 8: Evolution of the Premium to GDP ratio for the life and nonlife insurance sectors in the United States, 1995-2021



Source: AM Best.

Figure 8 shows parallel time trends in the evolution of insurance business for our two main insurance groups (life and nonlife) up to 2012 (especially from 2002 to 2011). Post-2012, insurance business diverges between the two groups. Figure 8 also indicates that insurance business declined as a proportion of GDP for the life insurance sector from the year 2012 onwards, while it increased slightly as a proportion of GDP for the nonlife insurance sector from the year 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 climate risk losses (Dionne and Desjardins, 2022).

6.4. The effect of fees charged on life insurance products and the decline in life insurance business during the post-2012 period

Fees charged represent the amount the insurer adds to the cost of the policy to cover the operating expenses of selling insurance, investing premiums, and paying claims.

Figure 9: Evolution of fees charged as a % of GDP and evolution of premiums collected as a % of GDP in the life insurance sector

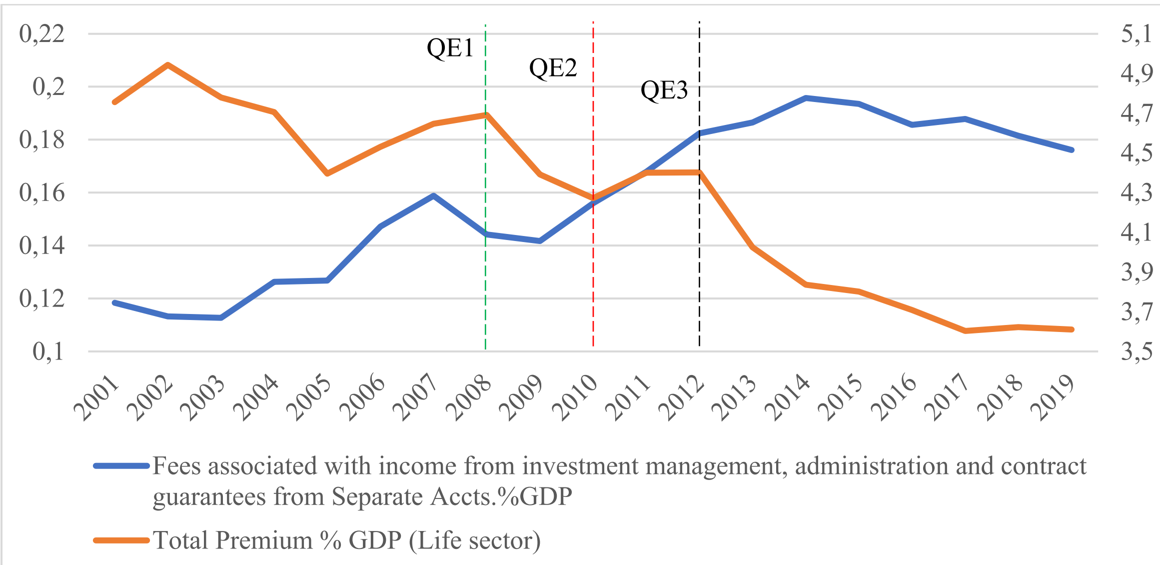


Figure 9 shows that fees charged to policyholders increased during the implementation of the two major quantitative easing measures that began after the 2007-2008 financial crisis and ended in 2012 (covering the period from 2009 to 2012). Figure 9 confirms our assumption according to which sales of life insurance products are a decreasing function of fees charged to policyholders.

To summarize, keeping interest rates low between 2009 and 2012 increased the fees charged to policyholders. This rise in fees between 2009 and 2012 led to a shock in sales of life insurance products, which caused sales to fall after 2012, as Figure 9 shows. In addition, as fees rose and rates remained low, many insurers stopped offering minimum return guarantees in response to the fall in T-bond interest rates to below 3% (minimum guaranteed rate) between 2012 and 2022 (marked by very low 10-year T-bond interest rates).

Conclusion

We analyze the evolution of M&A in the US insurance industry. We show that an interest choc related to the Fed monetary policy explains the loss of parallel trend in M&A between life and nonlife sectors, after 2012. We also document that the difference cannot be explained by climate risk events.

A significant drop of M&A was observed in the life sector and this drop is mainly observed in the variable annuity business. This is explained by a significant drop in interest rates that increased the cost of risk management for life insurance companies.

More research is still necessary to confirm the most significant cause of this results.

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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

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 reports the basic estimation[7] results of the Average Treatment on Treated (ATT) ($Treated_L$×Post2012) using the SDID 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&A per State-Year during the period 1990-2022. The treatment indicator is a dummy variable that take the value of 1 for the years during 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 ATT estimation relatively lower.

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

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

Note: *** 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.

Figures D1 and D2 give the M&A 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

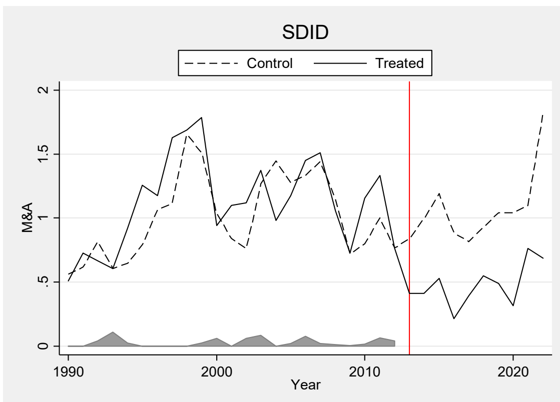
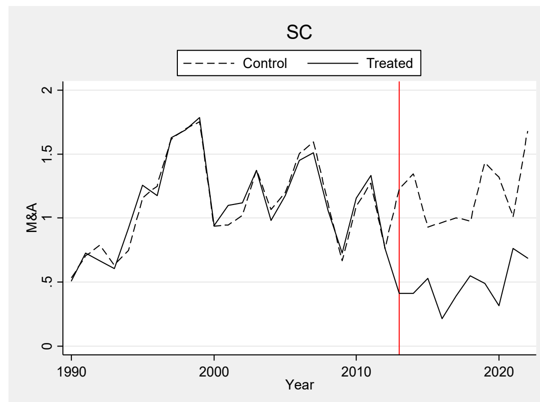


Figure D2



Notes: 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.

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&A 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&A per year for the control units predicts average M&A 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&A per State-Year for treated group and the average number of M&A 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

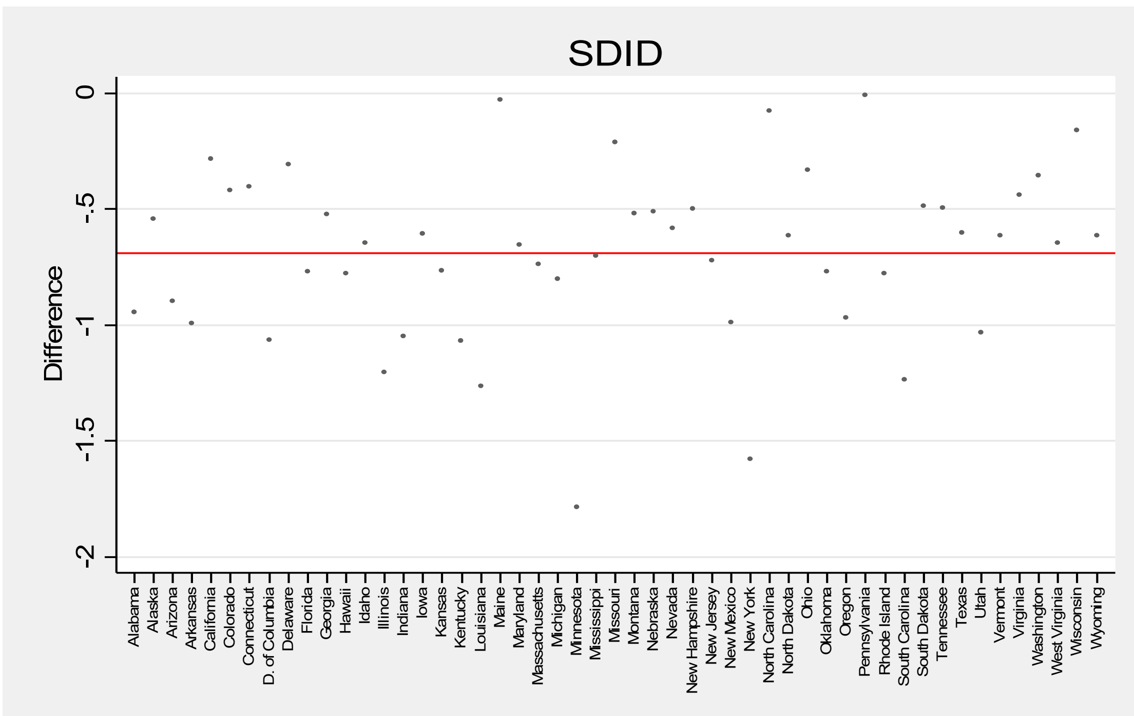
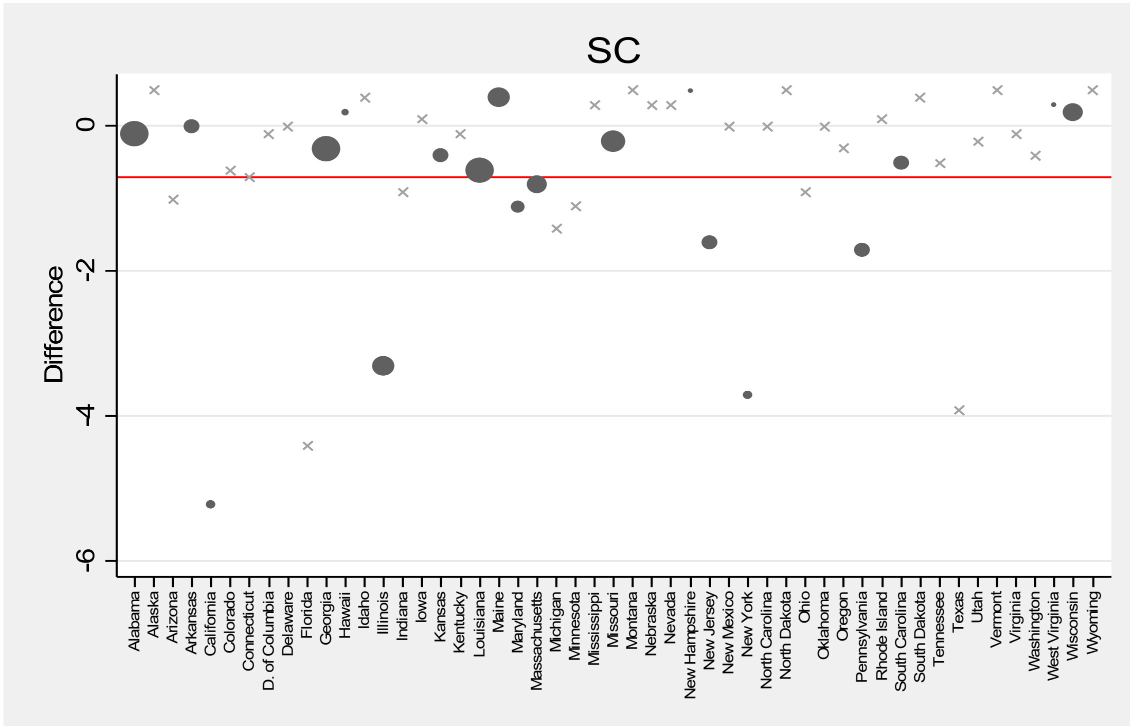


Figure D4: Unit-specific weights



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]

[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.

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 covariates. The estimation period is now from 2001 to 2019 due to the lack of detailed datasets for the direct written premium for each sector: Life, Health, and P&C. Comparatively to the estimated effect reported in Table D1, we observe that adding covariates reduces slightly the ATT with the SDID methods which is now around -0.67 and increases the estimated effect by the SC model to -0.80. The DID estimation gives a notably lower treatment effect.

Table D2: Estimation of the ATT using the SDID and SC models: Adding covariates from 2001 to 2019

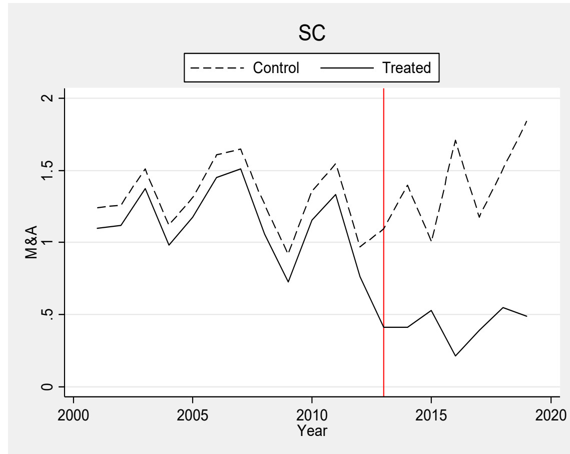
	(1)	(2)	(3)
Number of M&A by State-Year	SDID	SC	DID
$Treated_L \times Post2012$	-0.670***	-0.803***	-0.574***
	(0.204)	(0.294)	(0.211)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y
Year	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	1,938	1,938	1,938

Note: *** p<0.01.

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

Figure D5

Figure D6



Notes: 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.

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

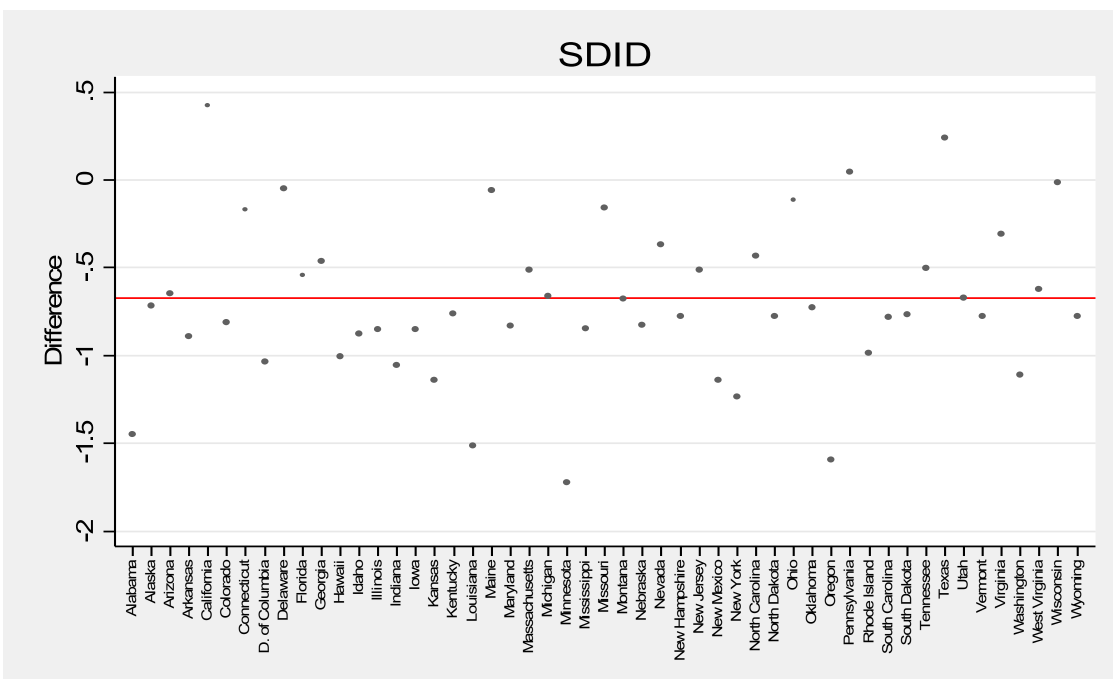
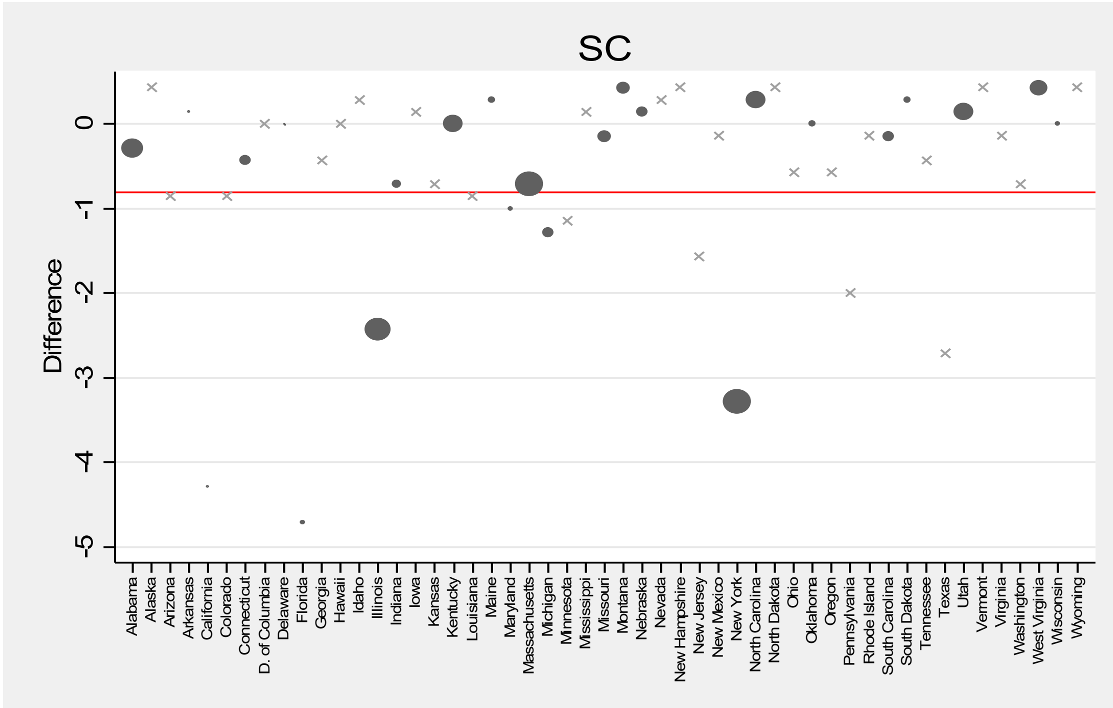


Figure D8: Unit-specific weights with covariates



We observe 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). 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 2001-2019, but without the covariates. The estimation results are reported in Table D3 and show that the estimated treatment effect for the SDID and the SC methods are quantitatively different from the estimated effects reported in Table D2, namely with covariates. It appears that the estimated treatment effect by the SDID and SC is very sensitive to the conditioning on time varying covariates. In the contrary, the DID estimation shows a relatively more stable estimated treatment effects with and without covariates.

Table D3: Estimation of the ATT using the SDID and SC models: Without covariates from 2001 to 2019

	(1)	(2)	(3)
Number of M&A by State-Year	SDID	SC	DID
$Treated_L$×Post2012	-0.706***	-0.739***	-0.593***
	(0.114)	(0.172)	(0.136)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y
Year	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	1,938	1,938	1,938

Note: *** p<0.01.

In the previous estimation, the control group consists of nonlife sector. Now, we decompose this control group into two separate sectors: Health and P&C. Next, 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 for the SDID and SC methods. However, the decrease 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

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

Note: *** p<0.01.

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

Figure D9

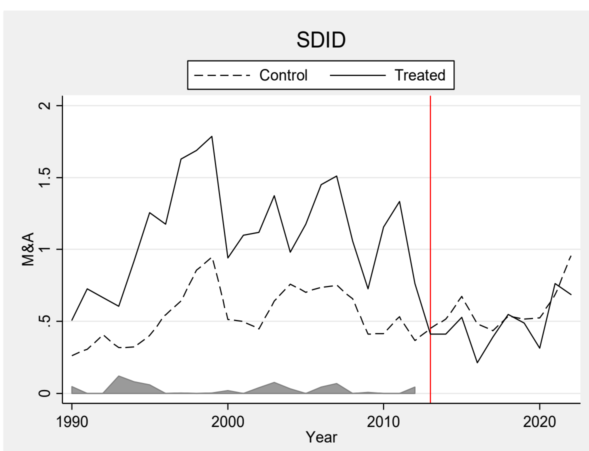
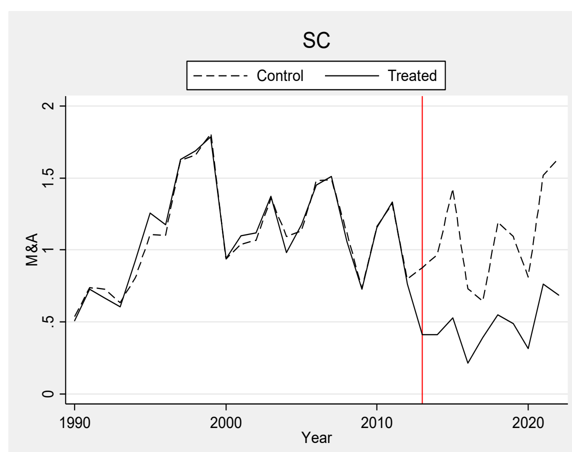


Figure D10



Notes: 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.

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 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 2019, 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 sector and P&C sectors as our control groups. For each sector, we then collect the premiums and the number of insurers by State-Year.

Table D5 reports the ATT estimation results with covariates and two control groups and show a statistically significant treatment effect but with lower magnitude as compared to the previous estimation (Table D4) and the baseline estimation (Table D1). Surprisingly, the SDID and the DID estimations give the same treatment effects. 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 without covariates for the period 2001 to 2019

Number of M&A by State-Year	(1) SDID	(2) SC	(3) DID
$\text{Treated}_{\text{L}}\times$Post2012	-0.633***	-0.470***	-0.663***
	(0.134)	(0.180)	(0.106)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y
Year	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	2,907	2,907	2,907

Note: *** p<0.01.

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

Figure D11

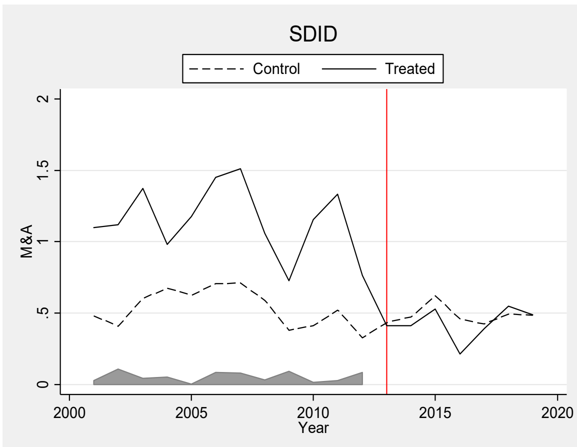
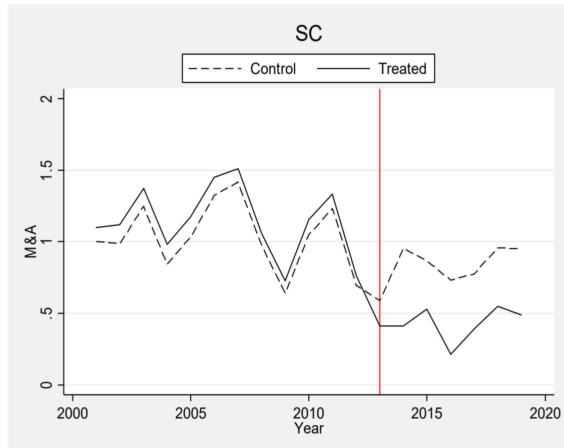


Figure D12



Notes: 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.

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 quantitatively different estimated treatment effects for the SC and the DID methods as compared to the estimation in Table D5. The SDID estimation leads to a relatively stable treatment effect in Table D5 and Table D6.

Table D6: Estimation of the ATT using the SDID and SC models: Two control groups and with covariates for the period 2001 to 2019

	(1)	(2)	(3)
Number of M&A by State-Year	SDID	SC	DID
$Treated_L$×Post2012	-0.623***	-0.518***	-0.629***
	(0.158)	(0.197)	(0.143)
Constant	Y	Y	Y
State fixed effect	Y	Y	Y

Number of M&A by State-Year	(1) SDID	(2) SC	(3) DID
Year	Y	Y	Y
Bootstrapped SE (Clustered at the State level)	Y	Y	Y
Observations (State-Year)	2,907	2,907	2,907

Note: *** p<0.01.

In sum, we find that the baseline estimation, namely DID with one control group and without covariates, gives qualitatively similar treatment effects by the two methods: SDID and SC. However, adding covariates into the estimation reduces notably the treatment effects for the three estimation methods. With two separate control groups, the DID estimation yields a similar treatment effect than the baseline estimation, however, the SDID and the SC give lower coefficients. Overall, we observe that the SDID and DID estimations give relatively similar results for the treatment effects in different empirical settings. In addition, it appears that the SDID and DID estimators for the treatment effect are more stable than the SC estimation which varies from -0.80 to -0.47 depending on the empirical setting. Table D7 summarizes the estimated coefficients 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	2001-2019 One control group With covariates	-0.670***	-0.803***	-0.574***
Table D3	2001-2019 One control group Without covariates	-0.706***	-0.739***	-0.593***

Table D4	1990-2022 Two control groups Without covariates	-0.651***	-0.614***	-0.680***
Table D5	2001-2019 Two control groups With covariates	-0.623***	-0.518***	-0.629***
Table D6	2001-2019 Two control groups Without covariates	-0.633***	-0.470***	-0.663***

Note: *** p<0.01.

Appendix E: Variable annuities and life insurers

- General description

A variable annuity is a contract between an insured and a life insurance company, in which the insurer agrees to make periodic payments to the insured, beginning immediately or at some future date (NAIC, 2023a)

The value of the investment varies depending on the performance of the investment portfolio. Investments are usually in mutual funds that invest in stocks, bonds, and money market instruments. Variable annuities differ from standard mutual funds, however, because they make periodic payments for the rest of insured life and have a death benefit. They are also tax deferred.

Variable annuities allow the insured to allocate part of payments to a fixed account with a fixed rate of interest. The insurance company may reset this interest rate periodically, and it usually provides a guaranteed minimum (e.g., 3% per year).

At the payout period, the insured can receive his revenue as a lump-sum payment or as regular payments at monthly intervals. Insured can choose to have annuity payments last for a period chosen or for an indefinite period. During the payout phase, payments can be fixed in amount or can vary according to the performance of the mutual fund.

If the insured withdraw money from his account during the early years of the accumulation phase, he may pay surrender charges. Surrender charges apply if the insured withdraw money from a variable annuity within a certain period after a purchase payment. A surrender is a type of sales charge. This charge is used to pay a commission for selling the variable annuity. There are other charges such as underlying fund expenses, mortality expenses, and administrative expenses.

- The 2008-2009 annuity crisis

The variable annuity crisis of 2008-2009 was related to the stock market (McKinsey, 2009). The period 2003-2007 was very profitable for the life insurance industry. The main driver of this success was the variable annuity market.

The 2008-2009 annuity crisis affected life insurance companies via their variable annuities (VA) business with exposure to equity markets. The total market capitalization of larger insurers decreased 58% with a loss amount of $36 billion. Many life insurers were downgraded. Significant decline in Treasury rates caused losses. In response many insurers raised prices or cut benefits for new businesses, which significantly reduced sales of annuities.

One advantage of VA is to offer tax-deferred savings. They were introduced for life insurance in 2005, a period of growing markets before the financial crisis that started in 2007. At that time, the annual average return on equity was 9%. In 2002 the share to equity was about 50% while by 2007 it was around 80%.

2008 was a very bad year for the stock market, the worst since the Great depression. Risk free interest rates were very low with some negative values for Treasury bills. Liquidity became very low in different markets. Many leading insurers experienced a decline in their stock price and their CDS spreads increased significantly.

- Variables annuities and captives (Du and Martin, 2014)

These authors provide an analysis of ten VA providers during the period 2008-2012. VA with guaranteed living benefits had a growth of 4,6 percent in the last decade in comparison with 0.84 for traditional life insurance products. Guaranteed Living Benefits (GLB) offered guaranties against market risk with a minimum return upon death.

After the financial crisis, equity markets recovered and demand for VA GLB returned. At the end of 2012, an increase of 46 % was observed. Since 2008, 84% of VA had 80% of VA GLB feature. The use of captives reduced the risk of these products and almost all insurers offering these products recovered the losses of the financial crisis. But many big insurers left this risky market.

Others introduced new risk management tools for protection against equity market risk. The concentration of the market increased significantly after the financial crisis and the level of capital did not increase very much, since the risk was transferred to captives. The use of captives did not necessary diversify risk in the overall life insurance market. It remained very concentrated among few very large providers of VA.

- How interest rates affect the insurance sector (NAIC, 2023b)

Interest rates risk is a significant factor in determining insurers' profitability. Typically, if interest rates increase, the value of a bond or other fixed-income investment will decrease. Although rate changes in either direction may affect the normal operations of an insurance company, an insurer's profitability typically rises and falls when interest rates increase or decrease. Historical analysis shows that the overall trend is for the insurance sector to increase profitability when there are rising interest rates.

Changes in interest rates can affect the assets of an insurance company. Because insurance companies have investments in assets such as bonds, as well as market interest rate-sensitive products for their customers, they are susceptible to any changes in interest rates. Drops in interest rates can decrease an insurance company's liabilities by decreasing its future obligations to policyholders. However, lower interest rates can make the insurance company's products less attractive, resulting in lower sales and, thus, lower income in the form of premiums that the insurance company has available to invest. The net impact on the company's profitability is determined by whether the decrease in liabilities is greater or less than any reduction in assets that is experienced.

The interest rate environment has a significant impact on many segments of the financial sector, including the insurance industry and especially the life insurance industry (NAIC, 2023b). Prolonged periods of low interest rates negatively affect the financial performance of life insurance firms in multiple ways. In late 2021, interest rates began rising quite rapidly.

After the 2007-2009 financial crisis, the Fed lowered the Federal Fund Rate (FFR) target to between 0% and 0.25%, where it remained until December 2015. This policy was specifically designed to lower interest rates to induce consumer and firm borrowing. The FFR is the rate banks charge each other for very short-term loans, so changes in the FFR often have a weak effect on longer-term interest rates. Indeed, following the drop in the FFR to nearly zero in 2008, longer-term interest rates did not significantly fall.

Having reached the zero lower bound for the FFR in 2008 and recognizing insufficient downward movement in longer-term interest rates, the Fed used the quantitative easing program (QE) (2008-2012), which consisted of large-scale purchases of long-term government bonds (e.g., ten-year Treasury bonds) and other securities mortgage back securities helped to push the benchmark 10-year Treasury yield down from 4.7% at the start of 2007 to 1.9% at the end of 2011. Further, in 2012, the Fed conducted "Operation Twist" in which it sold short-term Treasury securities, the proceeds with which it purchased longer-term Treasury securities. Operation Twist put further downward pressure on long-term interest rates.

- Implications of low interest rates for insurers

The low interest rate environment was a key concern for life insurers because their assets and liabilities are heavily exposed to interest rate movements.

Life insurers keep comparatively large balance sheets, and a substantial share of their assets (over 60% in the aggregate) are interest-earning bonds. With lower interest rates, investment earnings on bonds decline. In an effort to raise investment earnings, some life insurers shifted funds out of investment-grade bonds into inherently riskier but generally higher-earning assets, such as ABS, collateralized loan obligations (CLOs), derivatives, and real estate.

In addition, the earnings on some life insurance products, such as annuities and cash value life insurance policies, depend on the spread between what life insurers earn in interest and what they pay in interest to the customer. Many of these products have a guaranteed rate of return, which means the interest credited to the consumer by the life insurer is fixed. These payments can be variable but are more commonly fixed (guaranteed).

One important indicator is the spread between investment returns (net portfolio yield) and the guaranteed rates of payout on liabilities such as fixed annuities. The data from the annual statements of 563 life insurance companies for which reserves represented 96% of total industry life insurance reserves show a compression in the spread between the net investment portfolio yield and the guaranteed interest rate during the financial crisis, when the spread fell from 1.8% in 2007 to 1.15 percent in 2009. Spreads have remained historically low since the crisis, peaking at 1.39% in 2011. But the spread plummeted from 2018 to 2020 following global economic softening, followed by the COVID-19 pandemic. Specifically, the spread compressed to 0.63% in 2020 from 1.1% in 2018. It bumped up only slightly in 2021. Over 2018-2021, total industry reserves increased from about $3.6 trillion to $4.1 trillion (unadjusted for inflation).

Data suggest that while the low interest environment created spread compression on earnings, it did not materially impact life insurers' solvency. But it may have affected mergers and acquisitions.

The NAIC has been actively monitoring the interest rate environment.

Appendix F

Table F1: Variables, data sources and descriptions

Variable	Description	Data source
Annuity payments	Annuity payments of Annuity business line include benefit payments from annuity (Variable and Fixed annuity) contracts and other contract payments. (Expenditures)	NAIC database
Expenses Annuity	Operating expenses of Annuity business line include commissions to agents, home-and field-office expenses, taxes, and investment expenses. (Expenditures)	NAIC database
Variable Annuity contracts premium	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. In contrast to fixed annuities' guaranteed interest provision, policyholders assume the investment risk with variable annuities because they are separate account products that are valued at market every day. (Income)	NAIC database
Fixed annuity contracts premium	Fixed annuity contracts guarantee a minimum credited interest. For immediate fixed annuity contracts, annuitants receive a fixed income stream based, in part, on the interest rate guarantee at the time of purchase. For fixed deferred annuity contracts, the insurer credits a fixed interest rate to contributions in the accumulation phase and pays a fixed income payment in the annuitization phase. (Income)	NAIC database
Fees charged	Income from fees associated with investment management administration and contract guarantees from separate accounts. (Miscellaneous income)	ACLI Life Insurers Fact Book

Variable	Description	Data source
Net investment ratio	Net investment income to premiums received (Income ratio)	NAIC database
Combined Ratio	Combined ratio is the sum of the payments and the expense to premiums received. (Expenditures ratio)	NAIC database
T-bonds yield rate	T-bonds yield rate refer to government bonds maturing in ten years.	World Bank Database
Life expectancy	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.	World Bank Database
Credit-risk-free interest rate	Credit-risk-free interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator.	World Bank Database
GDP	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.	World Bank database