Public Health Crises, Product Pricing, and Risk Management: U.S. Life Insurance during the 1918–19 Influenza Pandemic*

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Abstract

Using a novel, hand-collected dataset of U.S. life insurance companies during the Influenza Pandemic of 1918–19, we show that high-exposure firms charged higher prices on new policies *vis-à-vis* less exposed firms. Since the pandemic surprisingly increased mortality rates among young adults, we argue that insurers used product pricing as a risk management tool to mitigate the probability of financial distress. Consistent with this channel, health shocks significantly impact firms' exit and entry decisions depending on a state's exposure to the disease. Finally, we show that competing explanations for the observed price differences find little support from the data.

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1. Introduction

Despite the recent COVID–19 outbreak drawing renewed attention to the importance of systematic public health crises for firms' decisions, there is little research on how firms change product pricing behavior after a public health shock.[1] These are decisions firms face and have significant implications for customers. Such an investigation can also uncover one of the channels through which pandemics could affect the real economy and product price movements. However, studying how such a shock propagates through firms and the economy requires granular data on prices and firm fundamentals. Data scarcity becomes even more prominent to the extent that systematic public health crises are rare events. To overcome this hurdle, we resort to history and explore one of the most severe health shocks in our recent past—the Influenza epidemic of 1918–19. We introduce hand-collected, firm-level data on the universe of U.S. life insurers. Crucially, in gathering data between 1911–22, we study the short and long-term effects of public health crises on a crucial pillar of the financial system.

Analyzing life insurance companies is valuable and informative for at least two reasons. First, health shocks affect these life insurers through increased liabilities due to death benefits paid to customers, coinciding with a stark decrease in future premium income. Second, health shocks can decrease the value of the insurer's investment portfolio. This multifaceted exposure to health shocks underscores one of our contributions on the effects of financial frictions, often limited to the asset side of insurers' balance sheets.

The 1918–19 Influenza Pandemic is a critical historical episode for our study because of the nature of the disease. Many young adults passed away (see, e.g., Taubenberger and Morens, 2006), creating a mismatch between expected and actual payouts for life insurers, as this cohort is generally of lower risk.[2] This feature could affect insurers' actuarial models and thus impact the price of new insurance policies. More importantly, in contrast to the recent COVID–19 crisis, the Influenza epidemic was a health shock that did not coincide with a recession (e.g., Benmelech and Frydman, 2020; Velde, 2020).

[1] One notable exception in the literature is Koijen and Van Nieuwerburgh (2020), who document the benefits of positive health shocks (e.g., advances in immunotherapies for cancer treatments) for life insurance companies.
[2] Similarly, on March 2, 2021, reporting on a new mutation of the SARS-CoV-2 virus in Brazil, the *Wall Street Journal* wrote that *"younger patients are being hit significantly more by COVID–19."* This indicates that recent and future health shocks could follow a similar pattern than the 1918 Influenza outbreak.

This feature conveniently deals with the downturn's confounding effects in the COVID–19 crisis studies, providing a cleaner identification of a health shock's impact on product pricing behavior.

Leveraging the richness of our data, we create a firm-level metric of *ex-ante* exposure to the pandemic shock. In a difference-in-differences (DID) empirical setting, we show that insurers more exposed to the pandemic charged higher prices relative to low-exposure counterparts. Firms seemed to have priced in the increase in perceived mortality risk in new insurance policies—as, during the outbreak, young adults experienced a surge in excess mortality, thus severely affecting this cohort's longevity. The observed price increase was not only statistically, but also economically significant. On average, the real difference between the two groups is striking 6.35%. This corresponds to a $117.51 difference in 1917-based dollars, which is equivalent to $2,345.05 measured in 2019 dollars.

Building onto the previous literature, we control for several important factors that can explain such pricing differences. Such factors include financial constraints (e.g., *ex-ante* leverage), product market conditions (e.g., *ex-ante* geographical diversification), and regulatory stringency (e.g., *ex-ante* state-specific regulation requirements). We find that the factors have limited explanatory power to explain pricing differences. Further, the evidence is robust to controlling for confounding effects stemming from World War I and a range of robustness tests, such as accounting for unobserved characteristics of retired and new insurers. Finally, we show that these results are robust to changing our baseline empirical design to alternatives, such as propensity-score matching (PSM) and instrumental variable (IV) regressions (see Appendix).

Overall, we argue that the observed price variation is more consistent with insurers making rational risk-management decisions than with abrupt changes in insurers' clientele.[3] Four pieces of empirical evidence confirm this hypothesis. First, we show that insurers were more likely to increase prices if they exhibited less (*ex-ante*) capacity to take on new policies, or had a more conservative risk profile in their investment strategies (e.g., relatively low proportion of their portfolio invested in bonds and mortgage loans). Second, high-exposure insurers were relatively more likely to exit affected states, potentially because of the (perceived) riskiness to operate in those states. Third, we show that both

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[3] Specialized publications from the life insurance industry show that policyholder characteristics did not change after the outbreak (see, e.g., *The Spectator* (1922); Short (2019)).

high and low-exposure insurers actually *increased* the supply of new policies.[4] Furthermore, insurers did not significantly change their investment portfolio after the pandemic. This, again, suggests that risk aversion is an unlikely explanation of the observed price variation between insurers. Finally, we highlight that the timing of price variations occurred at the *zeitgeist* of the Influenza Pandemic, when risk management responses would be the most crucial.

Our paper contributes to many branches of the literature. First, there is an extensive literature on the pricing behavior of insurers. However, it is unclear how a systematic public health shock can impact policy prices for insurers. The first reason is that the vast majority of this literature focuses on shocks of financial nature (e.g., Ge, 2021; Ge and Weisbach, 2021; Koijen and Yogo, 2015; Liu, 2019). Hence, our first contribution is to fill this literature gap by focusing on how a health shock impacts insurers' product pricing decisions.

The second reason insurers' price response in a pandemic is unclear is the conflicting answers from studies of life- *versus* non-life insurance companies. For instance, in life insurance studies, Koijen and Yogo (2015) and Ge (2021) report price decreases following adverse events that affected life insurers' financial constraints. Conversely, in non-life insurance studies, Cummins and Danzon (1997) report that general liability insurance prices *increased* in response to adverse shocks to capital during the 1980s crisis. Similarly, Froot and O'Connell (1999) show a positive relationship between catastrophe reinsurance prices and the actual occurrence of catastrophes. They show that a decrease in supply is the most influential factor driving price variation. Finally, Froot (2001) documents that policy prices *increase* following catastrophes in the market for catastrophe reinsurance. He also argues that supply forces, i.e., a drop in the number of newly issued reinsurance contracts, explain this price increase. Our study brings novel insights to this debate. Indeed, our findings are distinctive because we argue that firms mitigated their exposure to increase in mortality risks through higher product prices *while not decreasing* the supply of new policies.

Beyond prices, another body of research focuses on insurers' real and financial responses to adverse shocks. On financial responses, e.g., Ge and Weisbach (2021) show that insurers allocate their capital towards safer assets to increase financial flexibility in the face of adverse shocks. Interestingly, we find no significant effect of the pandemic on the life insurers' portfolio choices, which seems to be a

[4] If firms became more risk-averse as a result of Influenza, one would expect a decrease in the growth rate of new contracts.

distinctive feature of public health shocks *vis-à-vis* financial shocks. On the real-economy side, Che and Liebenberg (2017) document that insurers could react to an exogenous shock by exiting certain areas. We add to this literature by showing how public health shocks propagate to the real economy, influencing firms' exit and entry decisions in U.S. state markets.

Finally, we also contribute to the growing literature investigating the human and economic impacts of the 1918-19 Influenza Pandemic. Hilt and Rahn (2020) use the impact of Influenza as an instrument to explain liberty bond subscriptions and political outcomes. Clay et al. (2018) document the relation between air pollution and influenza mortality. Anderson et al. (2020) study the effect of the epidemic on the American banking sector. We add to this literature by uncovering how a crucial part of the U.S. financial sector responded to an unexpected increase in mortality risk caused by the pandemic.

Overall, the firm-level responses we study bear consequences of more aggregate nature: the financial system, local product markets, and consumers. The decisions are vital to affecting consumer's access to affordable life insurance policies when they need them the most. As such, our results also provide novel insights and implications for regulators and policymakers fighting the COVID–19 pandemic.

2. The Life Insurance Industry and the Influenza Pandemic: Historical Background

The American life insurance sector has a long history. In 1812, the first life insurer was incorporated in Pennsylvania. A century later, more than 300 active life insurers operated throughout the country, with more than $10 billion in outstanding insurance policies. By 1923, the outstanding amount of life insurance policies grew to $55 billion, making it an essential part of the U.S. financial system.

Between 1912–23, three types of companies offered life insurance. First, "ordinary insurers," which accounted for 80% of insurance in force in the U.S. (see U.S. Department of Commerce, 1958). Second, with around 15% of the life insurance market, "fraternal life insurers" (later called mutual insurers) were cooperative companies in which each member paid a flat fee relative to annual premiums to obtain benefits when other policyholders died. Finally, "industrial insurers" targeted low-income families and provided policies for relatively modest amounts. The latter group accounted for less than 5% of insurance in force in this period.

The increasing awareness of Americans of the contract's benefits—mitigating the financial impact of losing a family member—fueled the industry's growth. By 1918, with the end of World War I, more than 85% of U.S. households held at least one life insurance policy (Short (2019)). Nevertheless, specialized publications of the period document that the Influenza pandemic also helped to increase awareness. For instance, *The Spectator* reported on July 13, 1922, that:

> *"The world war and influenza epidemic (which was still more fatal) brought home to the average man the necessity for life insurance."*

Additional sources of increased awareness came from educational campaigns and distributions of life insurance benefits—through the payment of death claims and maturing of endowment policies.

2.1. Insurance Regulation

The insurance industry's growth also coincided with an increase in regulation. The sector was almost exclusively regulated by state governments, with two main objectives: ensuring solvency of insurers and consumer protection (e.g., oversight in pricing, coverage, or claims availability). The importance of regulation was also noted by various insurance newspapers. For instance, *The Weekly Underwriter* (1920) wrote in an editorial,

> *"[T]hose who have the interest of business at heart are co-operating in every way to prevent unscrupulous persons from engaging in this work. The various associations have taken a decided stand against "rebaters", "twisters", and "knockers". The State laws … assure the people that the business of life insurance must be maintained upon a sound financial bases and that the forms of contracts contain no invidiuous clauses"*

There was remarkable variation across states (e.g., *The Spectator*, 1917) in their regulatory stringency. Indeed, Stalson (1942) noted that laws put certain states (e.g. New York) "at a great disadvantage in competition". We visualize this cross-sectional variation in Figure 1, where we construct a stringency index from counting the number of regulatory requirements reported by *The Spectator* in every state in 1917. As one could see from Figure 1, Alaska, Nevada, and Hawaii were the least regulated states. In contrast, Oregon, Ohio, and Tennessee were the most regulated states. More specifically, Alaska had seven requirements relating to "annual statements, fees, penalties, and taxes, etc." A life insurer active in Oregon, conversely, had to comply with 30 different requirements.

[INSERT FIGURE 1 ABOUT HERE]

Another focus of regulators was maintaining the dominance of domestic insurers by enforcing rules and capital requirements for non-U.S. insurers. Foreign entities were required to demonstrate their commitment and had to invest in U.S.-based securities. As a result, around 1918, foreign life insurers represented a tiny share of total insurance in force (e.g., Wilkins, 2009). The marketing of American life insurance firms also highlighted nationalism. For instance, Fidelity Mutual Life advertised itself as "purely American," with "no foreign insurance or investments" (*The Spectator*, 1916).

2.2. Historical Background

Two pathbreaking global events in the first decades of the 20th century were the outbreak of the 1918-19 Influenza Pandemic and the end of World War I. For life insurance companies, it was no different. According to narrative evidence from the insurance newspaper *The Spectator* on April 27, 1922:

> *"When the United States was engaged in the World War, the life insurance companies of this country were passing through what was from an actuarial standpoint one of the hardest periods of their existence, since it was during those years that these companies were paying not only numerous war claims but also a very large volume of money daily went out from their reserves to beneficiaries of the influenza victims."*

Below, we provide more details about each event and, more specifically, how it affected the U.S. life insurance sector.

2.2.1. The Influenza Pandemic

The Influenza Pandemic was a global catastrophe that lasted from January 1918 to March 1920. In the U.S., around 675,000 people died after contracting Influenza, also known at the time as "Spanish flu." Strikingly, the disease killed more American citizens than all wars in the twentieth century combined (see Clay et al., 2019). The first wave spread unevenly through the U.S. Taubenberger and Morens (2006) find that the first wave's death rates were not remarkably abnormal despite the higher illness rates. The second (and deadlier) wave lasted from the end of August until December of 1918. Subsequently, a less severe third wave lingered through the Spring of 1919. There were minor local outbreaks after 1919. In 1922, *The Spectator* reported that:

> *"Since January 1, 1922, there have been 9,285 cases in New York City, resulting in 187 deaths (…) The disease now prevailing in New York City presents features of resemblance to Influenza but is of a much milder type than the great pandemics of 1889–90 and 1918–19."*

Just following the deadliest wave, in July 1919, New York-based life insurance companies formed the "Influenza Commission" and sent out warnings to its policyholders, signed by a firm's medical doctor. Such messages were distributed through local agents, urging people to *"go to bed immediately if they were stricken and call physicians."* Overall, a distinct feature of the 1918–19 Influenza Pandemic was that relatively more younger adults passed away (Taubenberger and Morens, 2006).

2.2.2. World War I

On April 6, 1917, the United States declared war on Germany and entered World War I (see, e.g., Verdickt, 2020). Henceforth, American veterans were able to purchase life insurance. Starting from the end of 1917, however, the Federal government became an essential underwriter of life insurance under the War Risk Insurance Act. The Bureau of War Risk Insurance was beneficial for existing life insurers since they were relieved from underwriting war-related mortality risk (Stalson, 1942).[5]

Although the Act curbed the bulk of war-related mortality risk for U.S. life insurers starting in 1917, they still had some exposure on their balance sheets. The importance of such claims was, however, small *vis-à-vis* Influenza-related claims.[6]

3. Data Sources and Summary Statistics

We hand-collect balance sheet data for all American life insurance companies between 1911 and 1922 using *The Spectator*'s Insurance Yearbook. The insurer-level data from the yearbook offers a brief history, balance sheets, profit and loss statements, asset-class composition of investment portfolios (e.g., stocks, or bonds), and the geographical presence of every life insurance company operating in the United States.

To gauge an insurer's geographical exposure before the pandemic, we collect the dollar amount of all outstanding policies in each state in 1917. We then match the insurer-level information with two additional data sources. First, we rely on Clay et al. (2019) for excess mortality data in U.S. cities in 1918. Using insurers' *ex-ante* presence in each state, we calculate the weighted average mortality rate

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[5] A detailed description of the origins of the Bureau of War Risk Insurance is in the 1920 Annual Report of the Director, Section 1, pp. 4–6, available online in https://www.va.gov/vetdata/docs/FY1920.pdf. Accessed in July 27, 2021.

[6] For instance, the *Insurance Press* reported that *John Hancock Mutual Life* paid out $3.8 million more to victims of Influenza than veterans' death claims in 1918. Influenza-related claims represented circa 24.2%, and World War I represented 7.9% of the total claims. Additionally, the *Insurance Press* reported that *National Life of Vermont*'s death claims in 1918 experienced a drop of $660,000 in reserves due to Influenza, and only $196,000 due to World War I.

for the insurers. This variable gauges the exposure of each insurer to the abnormal mortality spikes caused by the Influenza pandemic.

Second, we match our life insurer-level data with the location of military camps from Hilt and Rahn (2020). As discussed before, the end of World War I coincided with the Influenza epidemic and could still impact our findings—despite the War Risk Insurance Act broadly limited this risk exposure to insurers. Soldiers who went to the battlefield can apply for war risk insurance, leading to increased death benefits from 1918 onwards—albeit not related to Influenza. To account for how exposed an insurer is to war-related insurance, we use each insurer's headquarter (HQ) location to calculate its (minimum) distance to military camps. We assume that life insurers headquartered in cities closer to WWI military camps plausibly have a more significant fraction of military clientele and, as such, greater exposure to war-related insurance policies.

3.1. Sample Construction, Firm-Level Measure of Exposure, and Control Variables

We start with a sample of 382 firms. We exclude the life insurers that retired before (62 insurers) and incorporated after the outbreak (72 insurers). To identify insurers in financial distress, we rely on the rich narrative evidence in *The Spectator*. Furthermore, we require that insurers have at least one year of accounting information before December 1918. After these filters, we end up with 247 life insurance companies.

[INSERT FIGURE 2 ABOUT HERE]

Figure 2 presents the geographical distribution of insurers' business. It is clear from the figure that there is a dispersed distribution across the nation, with a notable presence in the Midwest. The states with the most insurance business are Illinois (9.32%) and Indiana (8.15%). Life insurers' geographical distribution is somewhat similar to that of NYSE-listed firms in the 1930s (Cortes and Weidenmier, 2019).

3.2. Summary Statistics

A crucial variable in our study is the price of life insurance policies. We divide the total dollar value of new policies by the number of new contracts to calculate the average policy price. We then adjust it with the CPI index to measure all values in 1917-based dollars. Therefore, our price variable is the average real price of newly issued life insurance policies. We adopt the standard control variables used in the life insurance literature (e.g., Koijen and Yogo, 2015):

- *Size*: logarithm of total admitted assets (*TAA*)
- *Asset growth*: the growth rate of *TAA*
- *Profitability*: total income minus total disbursements to *TAA*
- *Liquidity*: the sum of cash holdings, collateral loans, and premium notes divided by *TAA*
- *Leverage*: one minus the ratio of equity to *TAA*

We include three additional control variables specific to our purposes. First, to capture geographical diversification, we take the logarithm of the number of states in which a life insurer is active (*GEO*). Second, to capture insurer capacity, we divide the surplus by the value of newly issued insurance policies.[7] Finally, we introduce a firm-level regulation metric, using state-level regulatory stringency data depicted in Figure 1. We calculate an insurer's exposure to regulation stringency as the number of rules that firms had to comply with across all the states weighted by how important each state is for its business. To calculate the state weights for each insurer, we use the dollar amount of insurance in force in that specific state in 1917.

Table 1 presents our summary statistics. Panel A reports that the average real price of life insurance policies totaled $1,837.95 (7.516, in log scale).[8] The average firm had total admitted assets worth $1.9 million (14.466), grew by 15.80% per year, and sold life insurance policies in about nine states (1.567). The average insurer had a leverage ratio of 80.5%, consistent with the literature that focuses on the more recent period (Ge, 2021).

[INSERT TABLE 1 ABOUT HERE]

Additionally, we split the sample based on the mean life insurer-level mortality rate: more-exposed insurers experienced a mortality rate above the industry's average and *vice-versa*. In the last three columns, we study the differences between more-exposed *versus* low-exposed firms: highly exposed

[7] The capacity variable definition comes from "capacity-constraints theory" in the insurance literature (see, e.g., Gron, 1994; Winter, 1994). It predicts that insurance policy prices are inversely related to the firm's capacity. The premise of this theory is that firms follow underwriting cycles: periods of hard (with rising prices and reduced coverage) and soft markets (falling prices and increased coverage) alternate.

[8] This was significantly lower than the average policy of War Risk Insurance, which was aound $8,000 (Stalson, 1942).

insurers were, on average, larger (as measured by total admitted assets). They were also active in more states, exhibited higher leverage, lower operating profitability, and lower asset growth than their low-exposed peers.

Panel B of Table 1 reports the summary statistics of the investment portfolio of the average insurance company. Mortgage loans (49.2%) and bonds (19.1%) were the most important asset classes.[9][10] Real-estate (6.6%), stocks (1.3%), or collateral loans (0.8%) were less important. Overall, this composition is different from other countries during this period. For instance, the average British life insurer held more than 40% of their portfolio in bonds, whereas real estate accounted for less than 10% (Bogle et al., 2020). Similarly, French insurers held more than 40% of their assets in French government bonds relative to 20% in real estate (Hautcoeur, 2004).[11]

There were also investment strategy differences between high- and low-exposure life insurers. On average, high-exposed insurers invested more in bonds and stocks while holding fewer mortgages or collateral loans. Using Liu's (2019) definition of "risky holdings" (i.e., mortgage loans and bonds), high-exposed life insurers held significantly more risky assets (69.4%) relative to low-exposed firms (67.5%), a difference statistically significant at 5% confidence level.

[INSERT FIGURE 3 ABOUT HERE]

Figure 3 presents the growth rate in newly issued life insurance policies for high- and low-exposure firms. It shows a notable increase of 50% in the number of new life insurance policies in 1919. This increase confirms the narrative evidence presented in the earlier section about the greater awareness of the benefits of owning insurance policies. The growth rate in newly issued policies then decreased to +20% in 1920 and –20% in 1921.[12] More importantly, the difference between high and low-exposed firms is not statistically significant. This striking similarity in growth rates implies that, although the

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[9] The 1923 volume of *The Spectator* documents that life insurers mostly held government, municipal, and railroad bonds. Mortgage loans were classified as "farm" or "other." Unfortunately, this (detailed) information is not available before 1923.

[10] The 1917 volume of *Best* higlights there were only a limited number of insurers that held liberty bond subscriptions, such as the Central States Life Insurance Company, Great Southern Life Insurance Company, and National Life Insurance Company of the Southwest (see e.g., Hilt et al. (2021), Hilt and Rahn (2020)).

[11] In Australia, the same patterns occurred as in the UK and France. Around 1920, state-guaranteed bonds (49.6%) were far more important than real-estate mortgage loans (28.1%) or loans to policyholders (11.6%) (see, e.g., Keneley, 2006).

[12] *The Spectator* (1922) notes *"the year 1921 for the life insurance companies has been one that required courage (…) In fact, it has been a challenge to salesmanship."*

pandemic badly hit high-exposure insurers, they did not decrease the supply of policies. Indeed, *The Spectator* (1923) wrote:

> *"Immediately following the Influenza came a period known to the agency departments as the days of order-taking, a period during which no real salesmanship was necessary and during which business of companies grew by leaps and bounds, and practically every organization smashed all previous records."*

4. Empirical Strategy and Main Results

4.1. Difference-in-Differences Design

To better understand the effects of health shocks on the price of newly issued insurance policies, we use a DID specification:

$$p_{i,s,t} = \alpha + \beta_1(High\ Exposure_{i,s} \times Post_t) + \beta_2(Post_t) + \beta_3(Distance_{i,s} \times Post_t) + \gamma'(X_{i,s,t-1}) + \varepsilon_{i,s,t}, \tag{1}$$

where $p_{i,s,t}$ is the average price for insurer *i*, located in state *s*, at year *t*. *High Exposure* is an indicator variable that equals one if the insurer's weighted-average mortality rate is above the sector's average mortality rate, and zero otherwise. *Post* is an indicator variable that yields one from 1918 onwards, zero otherwise. *Distance* is the minimum distance insurers' headquarter are from a military base (see, e.g., Hilt and Rahn, 2020)). We add the interaction term *Post* × *Distance* to capture the effects of World War I, as discussed before. $X_{i,s,t-1}$ is a vector of lagged control variables, defined above. We add firm, state, and year-fixed effects to control for time-invariant sources of unobserved variation in product pricing. We cluster standard errors at the firm level. Our coefficient of interest is β_1, which measures the differential pricing effects of high-exposure *vis-à-vis* low-exposure firms after the outbreak.

4.2. Event Study Design

We also use an event-study specification to dissect the DID effect on prices on a year-by-year basis. To do so, we replace the *Post* variable in Eq. (1) with annual dummies interacted with the *High Exposure* variable. In this case, instead of the coefficient of interest being β_1 as above, our focus is the set of coefficients $\{\beta_t\}$, where $t = \{-4, -3, -2, -1, +1, +2, +3, +4\}$. In other words, these coefficients estimate the average treatment effects for the four years before and four years after 1918 (i.e., $t = 0$).

Before reporting the estimation results in the next section, it is important to recall why it is unclear how systematic public health shocks affect product prices for life insurers. Most of the literature focuses on the effects of financial frictions. For instance, Koijen and Yogo (2015) show that the main price trend was negative following the Great Recession. They find that price decreases were more substantial for life insurers with lower asset growth and higher leverage ratios. More recently, Ge (2021) reports that—to lure in customers—insurers reduced prices on policies that immediately convert into income. In another part of the literature, however, Froot (2001) shows that prices *increase* following the actual occurrence of catastrophes in the market for catastrophe reinsurance. He concludes that supply-side shocks explain this increase, that is, a decrease in the number of newly issued (re)insurance contracts and the heterogeneity in insurers' market power. Similarly, Cummins and Danzon (1997) report that general liability insurance prices increased during the 1980s crisis, which is characterized by adverse shocks to capital.

4.3. Main Results: The Impact of Public Health Shocks in Product Pricing

Table 2 reports the estimated DID coefficients in Eq. (1) of how firm-level exposure to the Influenza pandemic affected insurers' price changes. It has two main takeaways. First, in columns 1 through 3, we find a negative coefficient for *Post*, which corresponds to a negative secular effect in product prices. This finding implies that new policies' prices decreased for the average firm in the post-shock period. Indeed, the average firm's price falls by a considerable 25% after the outbreak. This result aligns with the previous findings from the life insurance literature, such as Koijen and Yogo (2015). We also confirm their findings that prices have a positive relation with size and asset growth and a negative association with leverage.

[INSERT TABLE 2 ABOUT HERE]

Second, and more importantly, we document a positive significant coefficient for the DID interaction *Post × High Exposure* in columns 1 through 3. This finding indicates that the negative secular trend is less pronounced for high-exposure insurers: they charge higher prices than their low-exposed peers. On average, the real difference between the two groups is striking 6.349%, significant at the 5% level. In terms of economic significance, this corresponds to a $117.51 difference in 1917 dollars. Measured in 2019 dollars, this is equivalent to $2,345.05. In sum, high-exposure firms are more likely to charge a higher price than low-exposure insurers. Taken together with the negative price trend, the positive relation between policy prices and insurer-level mortality is puzzling.

We then inspect the duration of the effect on price variation presented above using the event-study specification. As mentioned above, it allows us to dissect the average treatment effects for the four years before and after the pandemic outbreak. Figure 4 plots the event study coefficients.

[INSERT FIGURE 4 ABOUT HERE]

Figure 4 shows a significant price difference in 1918 and 1919, the *zeitgeist* of the Influenza Pandemic. Differences are statistically significant at the 5% and 10% level, respectively. A convenient feature of Figure 4 is to show that our DID design meets the usual requirement of "parallel trends" before the outbreak of the epidemic. Finally, we can see from Figure 4 that differences are no longer statistically significant from 1920 onwards, indicating that the price increase for high-exposure life insurers was temporary rather than permanent. Indeed, in 1922, *The Spectator* wrote an article about "The Loss Situation in New York":

"*The peak of high prices and excessive profits came in the year 1919. The beginning of the collapse in business was not recognized early in the year 1920 when it became apparent that there was no real recovery.*"

The article argued that insurers in New York, more heavily affected by Influenza, vastly increased prices in 1919. Interestingly, as shown earlier in Figure 3, the article also suggests the slowdown in newly issued policies' growth rates in 1920 and 1921.

Jointly, these results support the risk management hypothesis as a rational response from risk-averse managers: firms heavily hit by the pandemic adopted stricter risk-management practices. Managers could achieve this by charging higher prices, supplying lower quantities (i.e., shrinking newly issued policies growth rates), or doing both. Since Figure 3 showed that firms did not reduce the supply of life insurance policies, we argue that they achieved this by increasing prices.

Raising prices thus serves two purposes for a rational risk manager. First, the classical price mechanism reduces the likelihood of over-insuring (potentially riskier) clients, consequently avoiding future distress. Second, higher prices for new clients generate additional cash flows, which mitigate the probability of going bankrupt in the near term. However, other potential explanations compete with our risk management interpretation. We discuss them below in detail and further investigate them empirically in our robustness checks.

5. Discussion of Alternative Explanations, Heterogeneity, and Robustness Checks

5.1. Alternative Explanations

Financial Constraints. One alternative explanation is that an insurer's financial fragility is the sole driver of our results. If so, insurers' response to systematic public health shocks is no different from their response to financial crises, as studied by the earlier literature (e.g., Koijen and Yogo, 2015; Ge, 2021). Conversely, if the financial constraints do not fully explain the differences in pricing, our DID findings shown above should still maintain after adding other controls that proxy for firms' financial conditions. To test this hypothesis, we include two proxies of financial constraints (*ex-ante* leverage and liquidity) in our robustness checks. We follow Duchin et al. (2010) and measure these variables one year before the shock to mitigate endogeneity concerns.

[INSERT TABLE 3 ABOUT HERE]

Table 3 reports the estimated coefficients from the DID model focusing on the measures of financial constraints. As we can see from columns (1) and (2), the interactions with *ex-ante* leverage or liquidity are not statistically significant. This finding implies that these factors, on average, cannot explain the observed price differences between high or low-exposure firms.

Changes in Consumer Preferences. Another possible explanation for prices to increase is that new customers might prefer a different product mix after the Influenza outbreak. If people purchased a shorter-term policy, the life insurance literature predicts that average price of new insurance policies would increase, *ceteris paribus* (see e.g., Koijen and Yogo, 2015).

However, Koijen and Yogo (2015) argue that competition between life insurers would lead to a price war, reducing equilibrium prices. Given how homogeneous life insurance policies are, policyholders could choose to buy a policy from a firm operating in that same local market charging lower prices (e.g., low-exposure life insurers operating in the same locality as high-exposure insurers), so that an endowment effect (i.e., the willingness to pay more than a product's market price) would be unlikely in the life insurance market. Indeed, there is abundant historical evidence (see, e.g., *The Spectator* (1922) and Stalson (1942)) that competition was high in the market for life insurance.[13]

Despite these caveats, we run a robustness test in light of Koijen and Yogo's (2015) suggestion that this channel is modulated by how competitive a local life insurance market is. We control for firms' market share as proxied by the Herfindahl–Hirschman index (HHI).[14] Column (3) of Table 3 shows that adding the HHI does not alter our baseline results, i.e., the DID coefficient remains statistically significant.

Compositional Change in Customers' Age Groups. Another explanation for prices to increase is a change in the firm's customer composition. For example, if relatively older people were more likely to buy insurance, this would mechanically increase average prices.

Despite the richness of the life insurer-level data we use, one of our limitations is the lack of matched customer-insurer information to account for this channel directly. However, according to the recent literature, this channel is unlikely to explain our results. For instance, Short (2019) highlights little to no change in the characteristics of life insurance customers before and after the Influenza epidemic, including their age.

5.2. The Role of Regulation and Investment Portfolio Composition

In our description of the life insurance sector around the Influenza outbreak, we highlighted the heterogeneous characteristics of life insurers. We now consider the role of two important dimensions that vary widely across insurers (measured *before* the outbreak): state regulation and investment portfolio composition across broad asset classes.

First, as discussed in Section 2.1, there was remarkable variation between states in their regulatory stringency of the insurance industry. With this in mind, we add our *Regulation Index* as an additional regressor to our baseline specification. In column (4) of Table 3, we find that variation in the *ex-ante*

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[13] For instance, *The Weekly Underwriter* (1920) reports an elevated competition across life insurers: "*competition is on a friendly plane that cannot be equaled in any other line of business today. So-called business secrets (…) are no longer considered secrets.*"
[14] We calculate the HHI for life insurer i at the state level using the total admitted assets of insurer *i* relative to other insurers headquartered in the same state. Our results also hold when using HHI at the national level, i.e., when we calculate the HHI relative to all insurers, regardless of where they are headquartered. These results are available upon request.

regulation index does not drive product pricing differences. Thus, life insurers did not seem to adjust prices according to the regulatory requirements they faced across the U.S.

Second, as discussed in Section 3.2, there was also substantial heterogeneity in investment strategies. On average, high-exposed firms invested more in bonds and stocks while holding fewer mortgages or collateral loans. Using Liu's (2019) definition of "risky holdings" (i.e., mortgage loans and bonds), we showed in Panel B of Table 1 that high-exposed life insurers held significantly more risky assets relative to low-exposed insurers. To incorporate this into our analysis, we include the *Risky Holdings* variable to our specification and report the results in column (5) of Table 3.

Interestingly, we find a negative coefficient on *Post* × *Risky Holdings*, which corresponds to a negative relationship between *ex-ante* portfolio risk and product prices. This implies that newly-issued policy prices decreased for insurers that had a higher proportion of riskier assets in their portfolio. Insurers that were more conservative in their investment strategy before the onset of the Influenza pandemic increased prices significantly. This result also echoes the risk management channel as a driver of the observed price variation between high- and low-exposure firms.

5.3. Robustness Checks

5.3.1. Placebo Tests and Alternative Empirical Designs

To showcase that our conclusion is not driven by our choice of treatment, control groups, and timing of the outbreak, we re-estimate the DID model of Eq. (1). First, we define high-exposure firms alternatively as those that experienced mortality rates *one standard deviation* above the sector's mean. Second, we exclude life insurers that have a mortality rate between the industry's mean and median. Finally, we conduct two placebo experiments. While still distinguishing between insurers that were badly affected by the actual pandemic, we exclude observations from 1918 onwards and fictionally assume that the pandemic took place two or three years earlier (i.e., 1916 and 1915). Table 5 presents the results.

[INSERT TABLE 5 ABOUT HERE]

In column (1), we document that the qualitative conclusion holds. First, life insurers that were more exposed to the Influenza charged significantly higher prices than low-exposure firms. As one would expect, the economic magnitude of the pricing differential is larger than what we observe in Table 2. The average price difference between the groups is 10.63% (equivalent to $195.25 in 1917 dollars).

In column (2), we exclude a subsample of firms from the control group to allow for a more substantial difference between treatment and control groups. This enables us to better understand which life insurers were responsible for the observed price difference. Overall, we highlight that the conclusion holds: high-exposure life insurers charged significantly higher prices than low-exposure insurers. The economic magnitude, however, is smaller than previously estimated. On average, the real difference between treatment and control group is 5.02% or $92.27 (in 1917 dollars).

Finally, columns (3) and (4) report the results of the placebo experiment. As expected, we find that the DID coefficients are not statistically significant. Thus, it appears that the main evidence is not driven by alternative forces. In fact, there are two other interesting results from the placebo experiment. First, we find no negative secular trend: the coefficient *Post* is statistically insignificant. This suggests that, in the absence of an exogenous shock, the average insurer does not lower its price. Second, we find prices to be positive related to leverage and asset growth, as in Table 2 and previous research showing that life insurers' prices are related to these insurer-level characteristics (e.g., Koijen and Yogo, 2015).

5.3.2. Robustness to Including New Incorporations

Up to this point, we have focused on life insurers that had (at least) one year of accounting data prior to the outbreak of the 1918–19 pandemic. This implies that new life insurers are excluded from the sample. However, new life insurers are important for existing firms from a competitive perspective. In this section, we study the difference in prices between high or low-exposure firms relative to new incorporations. If our conclusion that highly-exposed firms charge higher prices continues to hold, this variation should be significant between the different subsamples.

[INSERT FIGURE 5 ABOUT HERE]

Between 1918 and 1922, there were 88 new insurers incorporated. Figure 5 plots the yearly variation in the number of new incorporations. Most of the incorporations started in 1919 (35.22%), which was (partly) the response to an increase in the demand for insurance policies. As in Figure 1, there is a strong presence around the Midwest – Iowa (13.04%), Kansas (10.14%), and Nebraska (10.14%) were the most important states for new insurers.[15] Since the geographical distribution of the new insuseres was similar to existing firms, their locational similarity helps to compare both groups. Interestingly, there is a strong relationship between the states with the most new incorporations and bankruptcies. The correlation between the two groups exceeds 0.40, which implies that new insurers fill the gap left by bankrupt life insurers.

[INSERT TABLE 6 ABOUT HERE]

In Table 6, we test the average differences in real prices between high- and low-exposure life insurers and new firms. More specifically, we split the sample into the *Post Pandemic* (1918–22), *During* (1918–19), and *After* (1920–22) period.

There is one main takeaway from this Table. During the outbreak, we document a significant price difference between high-exposure and new life insurers. In terms of the economic magnitude, the difference is almost twice as large as the difference between high- and low-exposure life insurers. Interestingly, we do not observe any significant differences between low-exposed and new insurers. This suggests that new life insurers were relatively similar to low-exposure firms in terms of pricing. Moreover, the significant price variation only occurred *during* the outbreak of the pandemic. In the period after the outbreak, we do not observe a significant price difference. This finding thus confirms our conclusions from Figure 4, that the price response was likely used as a risk management tool by high-exposed firms to mitigate the risk of future financial distress.

6. Additional Consequences of Life Insurers' Risk Management Channel

So far, we have documented a significant difference in price behavior between life insurers according to their exposure to the pandemic. One important question that remains is whether the risk management response to a public health shock affects other real and financial decisions beyond product pricing. Building on the previous literature, we focus on two different aspects: entry and exit decisions (see, e.g., Ashenfelter and Jurajda, 2021), and investment portfolio choices (see, e.g., Ge and Weisbach, 2021).

[15] See the Appendix for more information.

6.1. Entry and Exit Decisions

This section focuses on their entry and exit decisions across the country and, specifically, in affected and non-affected states. Breaking down our variable *GEO* to measure the entry (i.e., positive changes in *GEO*) or exit (i.e., negative changes in *GEO*) decisions in affected and non-affected areas, we run the following DID specification:

$$y_{i,s,t} = \alpha + \beta_1(High\ Exposure \times Post_t) + \beta_2(Post_t) + \beta_3(Distance_{i,s} \times Post_t) + \gamma'(X_{i,s,t-1}) + \varepsilon_{i,s,t}, \quad (4)$$

where $y_{i,s,t}$ is GEO measured for insurer i, located in state s, at year t, including all states ($GEO_{all\ states}$); including only affected states ($GEO_{affected\ states}$); or including only non-affected states ($GEO_{non\text{-}affected\ states}$). We define an "affected state" as one having a mortality rate above the country's average. Table 7 reports the estimated coefficients of the DID model.

[INSERT TABLE 7 ABOUT HERE]

There are two key takeaways from Table 7. First, the secular trend in each specification is statistically insignificant. Overall, this indicates that the average insurer does not increase its geographical reach after the public health shock. One explanation is that new incorporations met an increase in demand, making it less appealing for the existing firms to expand. Indeed, Stalson (1942) also noted that the average insurer did not expand geographically. Instead, insurers developed their product mix after 1922 by offering annuity policies, a business line that was unimportant during our sample period.

Second, and more importantly, we report a significant negative second-level interaction, *Post × High Exposure* among the affected states. In column (4), the estimated coefficient is –0.097. Combined with an insignificant secular effect, this coefficient entails that the average high-exposure firm exits one affected state. Interestingly, we show that this effect occurred in the period *after* the outbreak.

Seen through the lens of insurers' risk management, leaving affected states arguably decreases the probability of future financial distress. Similar to pricing differences, if firms become more risk-averse due to the pandemic, exiting a high-risk state can be seen as a rational business decision. Interestingly, columns (5) and (6) show that high-exposure life insurers were *not* more likely to enter less-affected areas. Therefore, systematic health shocks affect locational choices made by life insurers mainly through exit decisions, making high-exposure insurers leave more affected areas.

6.2. Investment Portfolio Choices

A recent, growing literature explores the role of life insurers as asset managers (e.g., Liu, 2019; Ellul et al., 2020; Ge and Weisbach, 2021). Indeed, in more recent times, insurers hold the equivalent of up to 40% of the U.S. GDP in their investment portfolios.[16] Shocks to these financial entities, therefore, can easily propagate to the real economy. Since most of the research focuses on financial crises, we explore the effect of a public health shock on the life insurers' portfolio choices. We run the following DID specification:

$$y_{i,s,t} = \alpha + \beta_1(High\ Exposure \times Post_t) + \beta_2(Post_t) + \beta_3(Distance_{i,s} \times Post_t) + \gamma'(X_{i,s,t-1}) + \varepsilon_{i,s,t}, \quad (5)$$

where $y_{i,s,t}$ is the proportion of bonds, cash, mortgage loans, real estate, and stocks to total admitted assets for insurer i, located in state s, at year t. Table 8 reports the regression results.

[INSERT TABLE 8 ABOUT HERE]

Overall, there are no significant differences between high- and low-exposure insurers following the outbreak of the Influenza Pandemic. This finding is somewhat expected since the U.S. economy did not collapse due to the Influenza Pandemic (see, e.g., Benmelech and Frydman, 2020; Velde, 2020). Hence, systematic public health shocks do not seem to propagate to the aggregate economy through financial markets if it does not coincide with a severe recession.

7. Concluding Remarks

We uncovered a new channel through which systematic public health shocks impact firms' product pricing decisions. Specifically, we show that insurers with high exposure to a mortality shock charge higher prices relative to low-exposure insurers. We argue that these product pricing changes can be seen as a response from life insurers' risk management in the face of a systematic public health shock. Since high-exposure firms did not decrease the growth in their supply of new policies, we conclude that price changes can be interpreted as a rational response of insurers using their risk management toolbox. Since the disease led to a surge in young adults' mortality, life insurers priced in the higher perceived mortality risks following the outbreak.

[16] In contrast, life insurers in our sample period held the equivalent of up to 8.3% of the U.S. GDP in 1917.

We showed that alternative explanations are unlikely to fully account for the pricing differences that we document and find little support in the historical record or the earlier literature. In our tests, we formally control for other confounding factors stemming from World War I and standard proxies of financial constraints. Our findings contrast with previous studies focused on purely financial shocks, which forecast a price decrease (see e.g,e Ge, 2021; Koijen and Yogo, 2015), and papers that focus on supply and demand shocks, who show that price increases through the change in the supply of new policies and market power (e.g. Froot, 2001; Froot and O'Connell, 1999).

We also uncover other interesting economic consequences from our findings. First, systematic public health shocks have a significant effect on exit decisions. High-exposed insurers were more likely to exit highly-affected states, while not entering less-affected ones. This response is arguably driven by a risk-management motive of insurers to decrease the likelihood of financial distress. Finally, unlike the "flight-to-safety" effect observed in investment portfolio decisions of life insurers suffering from financial shocks (e.g., Ge and Weisbach, 2021), we show that the Influenza pandemic did not impact life insurers' investment allocations across broad asset classes. This result lends credence to the view that the Influenza Pandemic, while devastating from a health perspective, had a limited impact on the U.S. economy (e.g., Benmelech and Frydman, 2020; Velde, 2020). Our paper establishes that this view is also plausible from a life insurers' investor perspective.

While our paper is the first to introduce novel, firm-level balance sheet data for the universe of the U.S. life insurance industry, we believe avenues for future research include analyzing more detailed data for other types of financial intermediaries to evaluate how systematic health shocks propagated through different branches of the financial system.

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Tables and Figures

Figure 1. Number of State-Level Regulations in the Life Insurance Sector

This figure shows for all US states the number of regulatory requirements that life insurance companies had to comply with one year before (1917) the Influenza pandemic outbreak. We construct our regulatory stringency index by counting each state's total number of regulations reported by *The Spectator*.

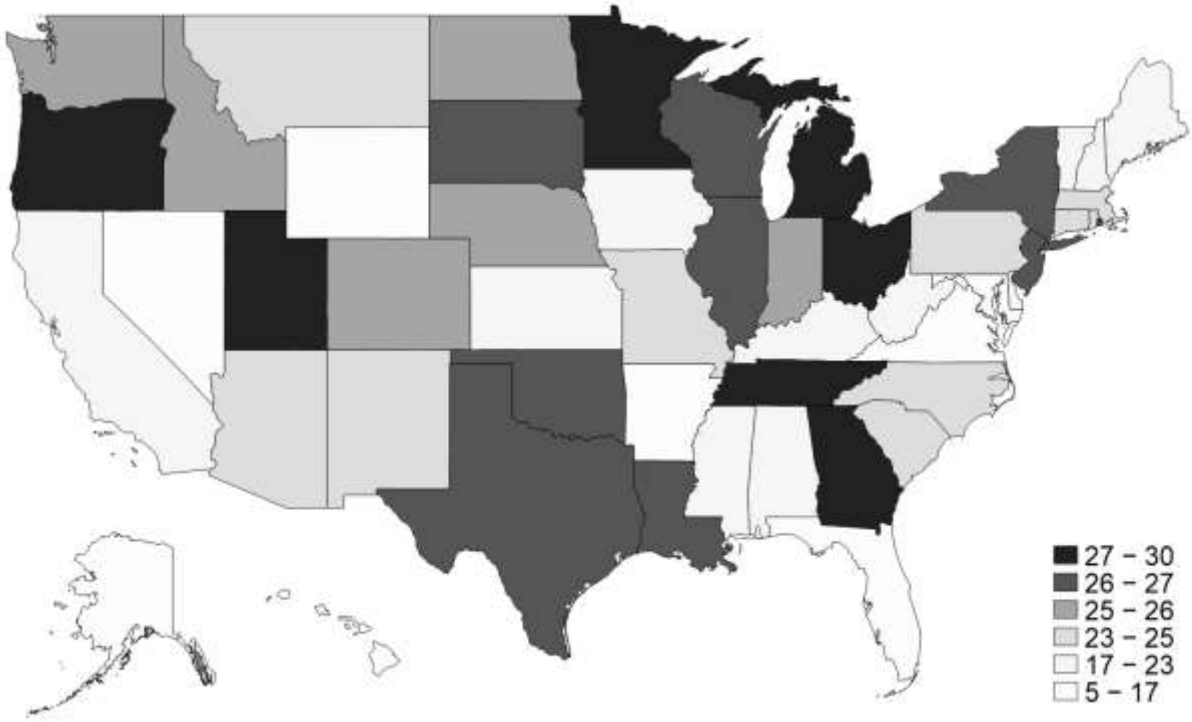

Figure 2. Geographical Distribution

This figure shows the distribution of the dollar value of life insurance policies outstanding for US life insurance companies in 1917, one year before the outbreak of the Influenza Pandemic. Source: *The Spectator*.

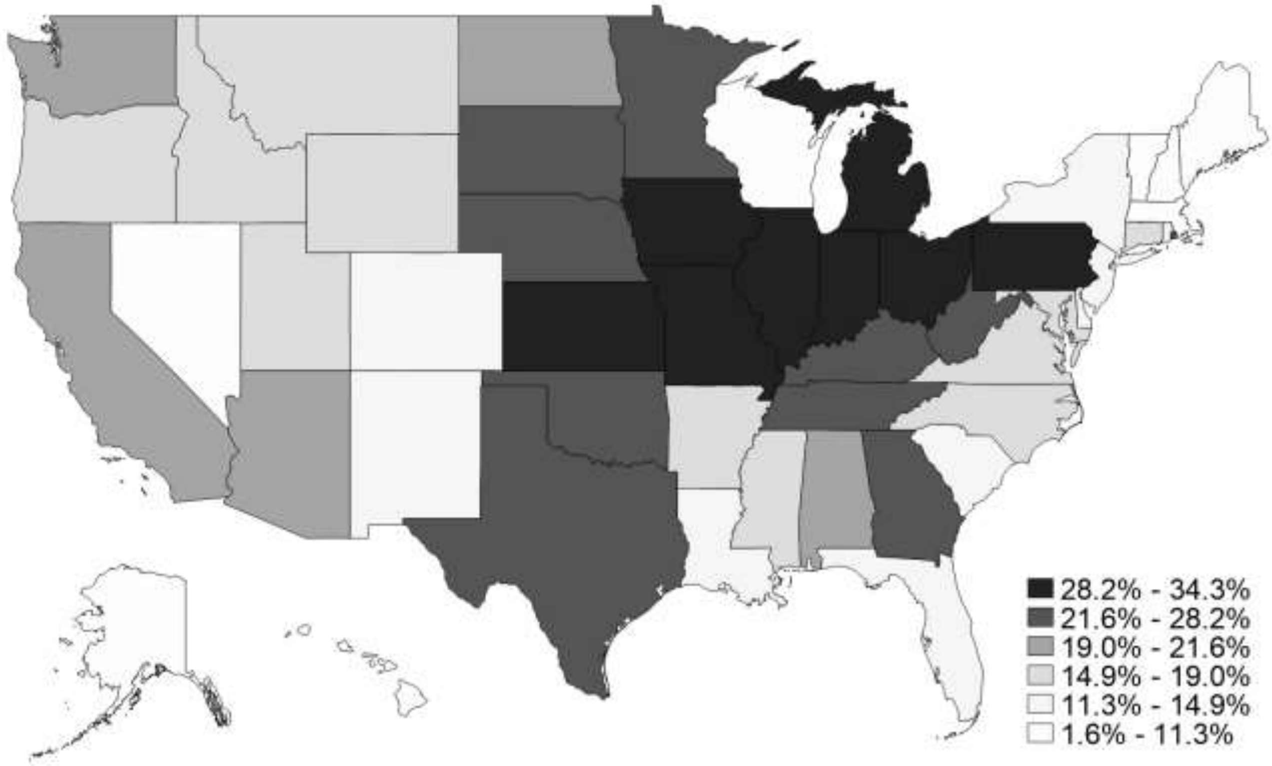

Figure 3. Growth Rate in Newly issued Insurance Policies: High- vs. Low-Exposure Insurers

This figure depicts the growth rates between 1912 and 1922 in the number of newly issued insurance policies for high- and low-exposure insurance companies. The vertical dashed line in 1917 indicates the Influenza pandemic outbreak. *High Exposure* is an indicator variable equal to one if the firm-level mortality rate is above the industry's average mortality rate. Source: *The Spectator*.

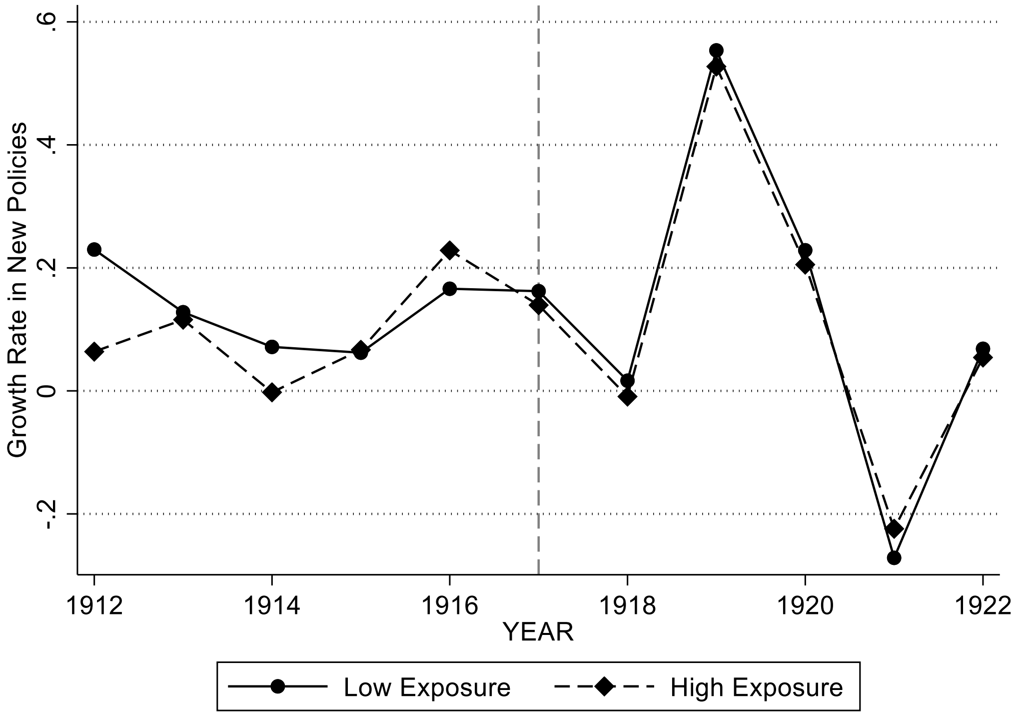

Figure 4. Event Study of Price Differences between High- and Low-Exposure Life Insurers

This figure shows the regression coefficients from a difference-in-difference regression of price on *High Exposure* and a set of lagged control variables, defined in Table 1. The dashed vertical line represents the transition between 1917 and 1918 (the outbreak of the Influenza Pandemic, that is, $t = 0$), and all other periods are relative to 1918 (e.g., $t = -1$ is 1917; t = +1 refers to 1919, etc.). The sample is annual and spans 1911–22. *High Exposure* is an indicator variable equal to one if the firm-level mortality rate is above the sector's average mortality rate. The black dots represent regression coefficients significant at the 5% level. The first (second) vertical line around the point estimates (dots) are confidence intervals at the 5% (10%) statistical significance level. Source: *The Spectator*.

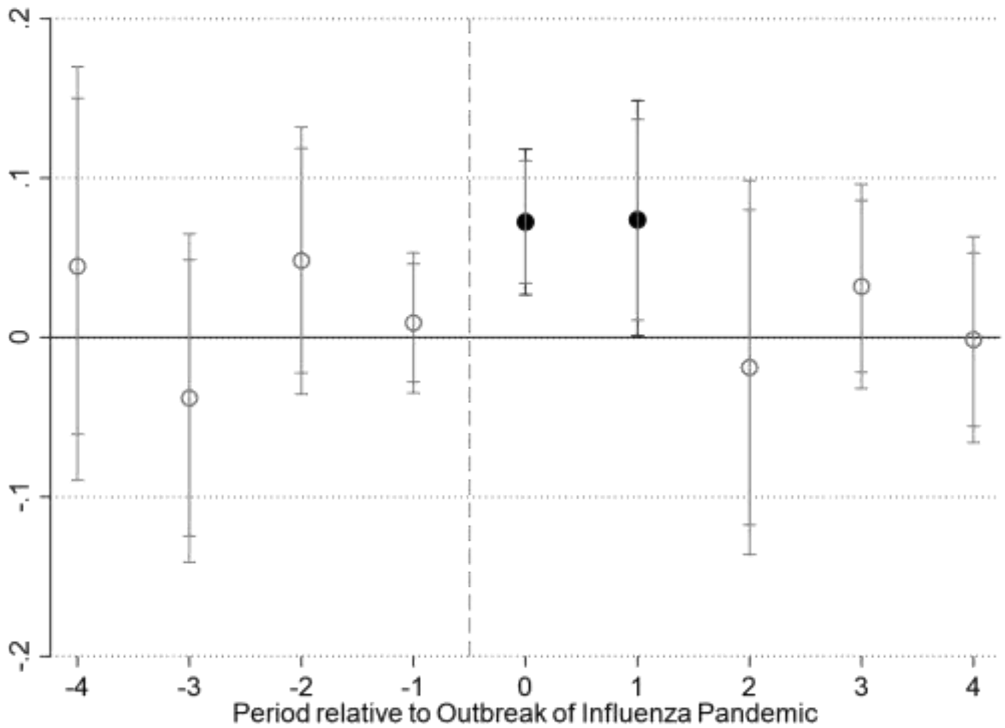

Figure 5. Total Number of Life Insurer Incorporations

This figure shows the number of new incorporations of insurers by year between 1911 and 1922. The shaded area highlights the 1918–19 Influenza Pandemic. Source: *The Spectator*.

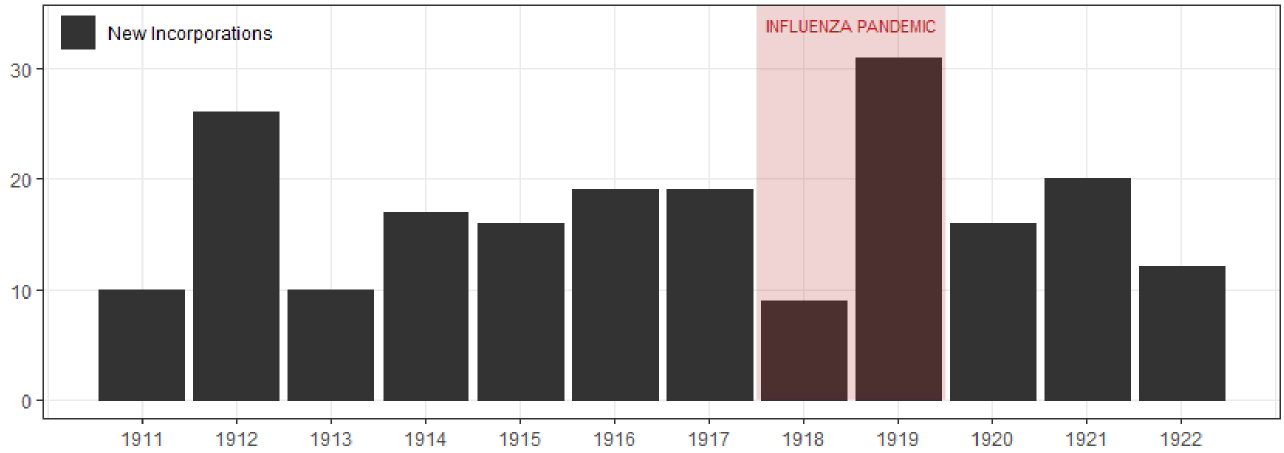

Table 1. Summary Statistics.

This table gives summary statistics for all relevant variables (Panel A) or investment portfolio (Panel B) for the full sample, high-exposure, and low-exposure life insurers. *High Exposure* is an indicator variable equal to one if the insurer-level mortality rate is above the industry's average mortality rate. *Asset growth* is defined as the growth rate in total admitted assets (TAA). *Capacity* is surplus divided by the dollar value of newly issued insurance policies. *GEO* is the log of the number of states where the insurer was active in. *Leverage* is calculated as (1 – Capital Stock to TAA). *Liquidity* is the cash holdings to TAA. *Mortality* is the insurer-level weighted-average mortality rate, with the proportion of life insurance policies in that state as the weight. *Price* is the dollar value of newly issued policies divided by the number of newly issued policies, divided by the CPI index. *Profitability* is the net income to TAA. *Regulatiom Index* is the log of the weighted-average number of regulatory requirements a firm has to comply with in any state, with the proportion of insurance policies in that specific state as the weight. *Size* is the log of TAA. *Bonds* is the bond holdings to TAA. *Real-estate* is owned real-estate to TAA. *Mortgage loans* is the real-estate mortgage loans to TAA. *Stocks* is the stock holdings to TAA. The last column gives, for each variable, the difference in the average. Two-sided *p*-values are reported in parentheses. Source: *The Spectator*. The sample period is 1911–22.

Panel A: Main Variables

	Full Sample		*High Exposure*	*Low Exposure*	*High vs. Low*
	Mean	Std. Dev.	Mean	Mean	*Difference*
Asset growth	0.158	0.151	0.128	0.173	-0.045***
					(0.000)
Capacity	0.216	1.158	0.333	0.156	0.177***
					(0.000)
GEO	1.650	1.139	1.910	1.387	0.523***
					(0.000)
Leverage	0.805	0.224	0.870	0.771	0.098***
					(0.000)
Liquidity	0.087	0.099	0.066	0.098	-0.032***
					(0.000)
Mortality	59.713	68.081	133.617	21.859	111.758***
					(0.000)
Price	7.516	0.572	7.538	7.459	0.078***
					(0.000)
Profitability	0.129	0.130	0.107	0.139	-0.032***
					(0.000)
Regulation Index	3.216	0.115	3.222	3.214	0.007
					(0.637)
Size	14.466	2.036	15.273	14.043	1.229***
					(0.000)

Panel B: Investment Portfolio

	Full Sample		*High Exposure*	*Low Exposure*	*High vs. Low*
	Mean	Std. Dev.	Mean	Mean	*Difference*
Bonds	0.191	0.207	0.281	0.144	0.137***
					(0.000)
Collateral Loans	0.008	0.043	0.006	0.009	-0.003*
					(0.073)
Real-Estate	0.066	0.126	0.071	0.063	0.008
					(0.104)
Mortgages Loans	0.492	0.273	0.415	0.532	-0.117***
					(0.000)
Stocks	0.013	0.057	0.020	0.009	0.011***
					(0.000)

Table 2. Product Pricing Response.

This table reports the coefficients from difference-in-difference regressions of the price on *High Exposure* and a vector of control variables, defined in Table 1. *Post* is an indicator variable that yields one from 1918 onwards. We add firm, state, and year fixed effects. We clustered standard errors at the firm-level. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Source: *The Spectator*. The sample period is 1911–22.

	(1)	(2)	(3)	(4)	(5)
Post	-0.286***	-0.295***	-0.226***	-0.291***	-0.227***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Post × High Exposure	0.054**	0.060**	0.062**	0.062**	0.049**
	(0.050)	(0.033)	(0.030)	(0.034)	(0.049)
Controls					
Post × Distance		0.002	-0.003	-0.002	-0.003
		(0.954)	(0.192)	(0.369)	(0.267)
Asset growth			0.071**	0.063*	0.073*
			(0.044)	(0.062)	(0.062)
Size			0.014	0.074**	0.039
			(0.589)	(0.014)	(0.218)
ROA			-0.009	-0.031	0.002
			(0.852)	(0.515)	(0.969)
Liquidity			-0.057	-0.030	-0.077
			(0.395)	(0.594)	(0.347)
Leverage			-0.302***	-0.231**	-0.374***
			(0.002)	(0.019)	(0.001)
GEO				-0.023	-0.018
				(0.245)	(0.394)
Capacity				-0.008	-0.001
				(0.628)	(0.953)
R-squared	0.220	0.209	0.220	0.289	0.220
Observations	2,519	2,340	2,018	2,000	1,782
Fixed effects	Yes	Yes	Yes	Yes	Yes
Excl. retired insurers	No	No	No	No	Yes

Table 3. Product Pricing Response: Alternative Explanations and Heterogeneity.

This table reports the coefficients from difference-in-difference regressions of the price on *High Exposure* and a vector of control variables, defined in Table 1. *HHI* is defined as the HQ-state-level Herfindahl–Hirschman index. *Demand Exposure* is defined as the dollar value of policies that are terminated if customers lapsed, surrendered, and changed their policy in year *t* scaled by all policies in force in year *t* – 1 for insurer *i*. *Risky Holdings* is the sum of bond holdings and mortgage loans to total admitted assets. *Post* is an indicator variable that yields one from 1918 onwards. The interaction terms for proxies of market factors are fixed one year prior to the outbreak. We include firm, state, and year fixed effects. We cluster standard errors at the firm level. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Source: *The Spectator*. The sample period is 1911–22.

	(1)	(2)	(3)	(4)	(5)
Post	-0.477***	-0.309***	-0.318***	-0.526*	-0.288***
	0.000	0.000	0.000	(0.099)	0.000
Post × High Exposure	0.061**	0.068**	0.070**	0.067**	0.083***
	(0.041)	(0.018)	(0.015)	(0.024)	(0.003)
Additional Controls					
Post × Leverage	0.178				
	(0.127)				
Post × Liquidity		-0.165			
		(0.166)			
Post × HHI Index			-0.001		
			(0.983)		
Post × Regulation Index				0.191	
				(0.513)	
Post × Risky Holdings					-0.114*
					(0.080)
Baseline Controls					
Post × Distance	-0.002	-0.002	-0.002	-0.002	-0.001
	(0.330)	(0.419)	(0.478)	(0.470)	(0.514)
Asset growth	0.021	0.023	0.024	0.028	0.028
	(0.656)	(0.631)	(0.612)	(0.569)	(0.553)
Size	0.047*	0.043	0.04	0.039	0.029
	(0.081)	(0.108)	(0.138)	(0.167)	(0.318)
ROA	-0.034	-0.053	-0.049	-0.049	-0.047
	(0.513)	(0.312)	(0.341)	(0.345)	(0.369)
R-squared	0.279	0.277	0.277	0.275	0.279
Observations	2,049	2,048	2,049	1,992	2,049
Fixed effects	Yes	Yes	Yes	Yes	Yes

Table 5. Robustness Tests

This table reports the coefficients from difference-in-difference regressions of the price on *High Exposure*, and a vector of control variables, defined in Table 1. In column 1, we change the treatment group to include all insurers that exhibited a firm-level mortality rate above one standard deviation above the industry's mean. In column 2, we change the control group by excluding insurers that exhibited a firm-level mortality rate between the industry's mean and median. In columns 3 and 4, we change the treatment time to, respectively, 1915 and 1916, and exclude all observations from 1918 onwards. *Post* is an indicator variable that yields one from 1918 onwards. We include firm, state, and year fixed effects. We cluster standard errors at the firm level. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Source: *The Spectator*. The sample period is 1911–22.

	Changes in Treatment Group	*Changes in Control Group*	*Placebo Experiments: Changes in Treatment Timing*	
	(1)	(2)	(3)	(4)
Post	-0.274***	-0.246***	-0.009	-0.019
	(0.000)	(0.000)	(0.536)	(0.328)
Post × High Exposure	0.101**	0.049*	0.103	0.082
	(0.012)	(0.095)	(0.250)	(0.130)
Controls				
Asset growth	0.068**	0.054	0.126**	0.111**
	(0.043)	(0.187)	(0.022)	(0.040)
Size	0.070**	0.066**	-0.125***	-0.118**
	(0.021)	(0.046)	(0.009)	(0.031)
ROA	-0.027	0.000	0.087	0.064
	(0.569)	(0.997)	(0.449)	(0.578)
Liquidity	-0.028	0.009	0.039	0.039
	(0.616)	(0.853)	(0.477)	(0.474)
Leverage	-0.262***	-0.260***	-0.444***	-0.401***
	(0.006)	(0.006)	(0.005)	(0.005)
GEO	-0.004	-0.024	0.009	0.009
	(0.193)	(0.273)	(0.720)	(0.720)
Capacity	-0.011	-0.011	0.037	0.035
	(0.562)	(0.527)	(0.213)	(0.198)
Post × Distance	-0.000**	-0.003	0.000	0.000
	(0.022)	(0.289)	(0.818)	(0.505)
R-squared	0.237	0.311	0.151	0.124
Observations	1,998	1,652	928	928
Fixed Effects	Yes	Yes	Yes	Yes
Treatment Year	1918	1918	1916	1915

Table 6. New Incorporations

This table presents descriptive statistics for high-exposure, low-exposure, and new life insurers' prices. The table reports the average price from 1918 onwards, including the difference between all different groups. *High Exposure* is an indicator variable equal to one if the insurer-level mortality rate is above the industry average mortality rate, zero otherwise. *During* is an indicator variable that yields one for 1918 and 1919, and zero otherwise. *After* is an indicator variable that yields one from 1920 onwards, and zero otherwise. Two-sided *p*-values are reported in parentheses. ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Source: *The Spectator*. The sample period is 1911–22.

	High Exposure (I)	*Low Exposure* (II)	*New* (III)	*Difference* (I – III)	*Difference* (II – III)	*Difference* (I – II)
Post Pandemic	5.064	4.969	5.004	0.060	-0.035	0.095***
				(0.281)	(0.456)	(0.000)
During (1918– 19)	5.093	4.989	4.877	0.216*	0.112	0.104***
				(0.071)	(0.274)	(0.001)
After (1920–22)	5.033	4.948	5.027	0.006	-0.079	0.085**
				(0.933)	(0.159)	(0.025)

Table 7. Entry and Exit Decisions.

This table reports the coefficients from difference-in-difference regressions of *GEO* on *High Exposure* and a vector of control variables. In columns 1 and 2, GEO is the log of the number of states where insurer *i* does business. In columns 3 and 4, GEO is the log of the number of affected states where insurer *i* does business. In columns 5 and 6, GEO is the log of the number of non-affected states where insurer *i* does business. *High Exposure* is an indicator variable equal to one if the insurer-level mortality rate is above the industry average mortality rate, zero otherwise. *Post* is an indicator variable that yields one from 1918 onwards. *During Outbreak* is an indicator variable that equals one for 1918 and 1919. *After Outbreak* is an indicator variable that yields one from 1920 onwards, zero otherwise. We include firm, state, and year fixed effects. We cluster standard errors at the firm level. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	$GEO_{all\ states}$		$GEO_{affected\ states}$		$GEO_{non\text{-}affected\ states}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.078		-0.035		-0.053	
	(0.427)		(0.213)		(0.214)	
During (1918–19)		-0.098		-0.089		-0.016
		(0.191)		(0.302)		(0.581)
After (1920–22)		-0.059		-0.016		-0.053
		(0.558)		(0.890)		(0.235)
Post × High Exposure	-0.005		-0.067		0.031	
	(0.918)		(0.213)		(0.144)	
During × High Exposure		0.038		-0.030		0.031
		(0.411)		(0.526)		(0.114)
After × High Exposure		-0.038		-0.097*		0.032
		(0.535)		(0.073)		(0.231)
Controls						
Post × Distance	-0.000	-0.000	0.000	0.000	-0.000*	-0.000*
	(0.430)	(0.420)	(0.362)	(0.371)	(0.075)	(0.075)
Asset growth	-0.129**	-0.131**	-0.142*	-0.144*	0.023	0.023
	(0.034)	(0.032)	(0.097)	(0.094)	(0.544)	(0.545)
Size	0.351***	0.347***	0.279***	0.274***	-0.005	-0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.856)	(0.858)
ROA	0.049	0.054	0.031	0.033	0.014	0.014
	(0.351)	(0.312)	(0.479)	(0.437)	(0.620)	(0.622)
Liquidity	0.019	0.027	0.074	0.078	-0.003	-0.003
	(0.860)	(0.812)	(0.569)	(0.548)	(0.959)	(0.958)
Leverage	-0.098	-0.109	-0.049	-0.062	0.012	0.012
	(0.557)	(0.509)	(0.814)	(0.771)	(0.891)	(0.890)
Capacity	-0.023	-0.024	-0.024	-0.025	-0.027***	-0.027***
	(0.409)	(0.394)	(0.348)	(0.329)	(0.000)	(0.000)
R-squared	0.145	0.146	0.145	0.146	0.028	0.028
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,046	2,046	2,046	2,046	2,046	2,046

Table 8. Portfolio Choices

This table reports the coefficients from difference-in-difference regressions of portfolio holdings and a vector of control variables, defined in Table 1. *Post* is an indicator variable that yields one from 1918 onwards. We add firm, state, and year fixed effects. We clustered standard errors at the firm level. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Source: *The Spectator*. The sample period is 1911–22.

	Bonds	*Liquidity*	*Mortgage Loans*	*Real Estate*	*Stocks*
	(1)	(2)	(3)	(4)	(5)
Post	0.045**	-0.019	-0.063	-0.009	0.005
	(0.019)	(0.249)	(0.250)	(0.655)	(0.705)
Post × High Exposure	-0.001	0.007	-0.001	-0.005	0.007
	(0.953)	(0.355)	(0.975)	(0.690)	(0.136)
Controls					
Post × Distance	-0.000	0.000	0.000	-0.006**	-0.000
	(0.708)	(0.394)	(0.412)	(0.031)	(0.987)
Asset growth	-0.004	-0.019	0.004	-0.017	0.001
	(0.795)	(0.199)	(0.917)	(0.243)	(0.822)
Size	-0.011	-0.008	-0.023	-0.019	-0.007
	(0.408)	(0.510)	(0.631)	(0.233)	(0.455)
ROA	-0.035	-0.000	-0.018	-0.002	0.003
	(0.207)	(0.986)	(0.558)	(0.898)	(0.498)
Leverage	-0.013	-0.030	-0.031	-0.070	0.003
	(0.768)	(0.338)	(0.784)	(0.235)	(0.790)
GEO	-0.009	0.0006	-0.028	0.014	-0.001
	(0.244)	(0.300)	(0.617)	(0.147)	(0.557)
Capacity	-0.001	-0.012**	-0.007	-0.001	0.011***
	(0.932)	(0.011)	(0.690)	(0.901)	(0.006)
R-squared	0.116	0.036	0.042	0.020	0.023
Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,049	2,027	2,049	2,044	2,025