Underwriting, Investing and Value: Evidence from Simulation and from Market Data

Nicos A. Scordis

Abstract: This study draws on established literature to frame the hypotheses that a property-casualty insurer generates value from its underwriting operations. The study relies both on results from a multi-period simulation of an insurance firm and on results from regressions using two panels of data on publicly traded property-casualty insurers. The study's results suggest a positive relation between underwriting performance and value regardless of the period of analysis. When investing performance is scaled by the risk-free rate, its relation to value is neutral or negative, depending on the period of analysis. An explanation for the study's findings is that property-casualty insurance firms have a comparative advantage in underwriting. By comparison, regulatory and operational constraints prevent the investing operations of these insurers to replicate benefits like those associated with levered investment trusts. An unexpected finding is that the ability of a property-casualty insurer to generate revenue amplifies the impact of underwriting performance on value. The study concludes with a discussion of the strategic implication of its results. [Keywords: Underwriting, investing, insurer.]

INTRODUCTION

Property-casualty insurers are a significant part of society and strong contributors to the economy. Yet, how these insurers generate value is still unclear. The literature recognizes that both underwriting and investing operations contribute to accounting profit (Forbes, 1970; Fairley, 1979; Myers and Cohn, 1987; Chen and Hamwi, 2000). The individual contribution of underwriting and investing operations to value, however, remains a matter of conjecture. Thus, this study contributes to the literature by directly investigating the relation of underwriting and investing opera-

1School of Risk Management and Insurance, Peter J. Tobin College of Business, St. John’s University, scordisn@stjohns.edu.
tions to the value of a property-casualty insurer. Surprisingly, such direct investigation appears to be a first.

The established literature supports two alternative hypotheses. The first hypothesis is that underwriting operations create value for property-casualty insurers. Thus, the performance of underwriting operations should be positively related to a property-casualty insurer’s value. While there are parallels between the use of policyholder funds by insurers and the use of debt by levered investment, the literature only supports the argument that, at best, property-casualty insurers invest on the efficient frontier. Thus, the performance of investing operations should be neutral to, or negatively related to, a property-casualty insurer’s value.

The study develops these hypotheses in its Literature Review and Hypotheses section. I argue that property-casualty insurers have a comparative advantage in managing underwriting risk but not investing risk. Schrand and Unal (1998) term risks over which a firm has a comparative advantage, and thus are able to generate value, core risks. The literature clearly identifies underwriting operations as a core risk (see for example Doherty and Schlesinger, 1983, or Gatzert and Schmeiser, 2012). There is disagreement in the literature, however, whether investing can be a core risk for property-casualty insurers (see for example Hofflander and Drandell, 1969; Hammond, Melander, and Shilling, 1976; Venter, Gradwell, Ashab, and Bushel, 1998). The section Results from Simulation Modeling develops a multi-period, stochastic simulation model of a stylized insurer. The simulation model induces variation in underwriting and investing performance by altering selected input variables one at a time over a specified range. The results of this variation allow observation of how value changes with changes in underwriting and investing under controlled conditions. The section Results from Regression Estimators investigates how value changes with changes in underwriting and investing by analyzing actual (rather than simulated) data from panels of quarterly observations from two different operating environments. The section Conclusions and Implications summarizes the study and its findings and discusses what the results might imply for the future ability of property-casualty insurers to generate value.

All of the study’s results suggest a positive relation between a property-casualty insurer’s underwriting performance and value. However, in the 2013–2016 data panel, where the risk-free rates are uncharacteristically low, the relation between investing performance and value is negative, while this relation is positive in the 1998 to 2006 data. When investing performance is scaled by the risk-free rate, the balance of the evidence suggests either a neutral or a negative relation between investing performance (relative to the risk-free rate) and value. An unexpected finding is
that the ability of a property-casualty insurer to generate revenue amplifies the impact of underwriting performance on value.

The inferences drawn from the results of this study are consistent with a competitive environment where information drives value. Insurers have a comparative information advantage in underwriting. The informational advantage of the average property-casualty insurer, however, faces potential threats from on-going changes in the insurance market—such as technology platforms with access to increasingly better data. Erosion in the ability of property-casualty insurers to generate value is dangerous both for the insurance market and for society that depends on this market working well.

**LITERATURE REVIEW ON THE HYPOTHESES**

The underwriting operations of insurance firms begin with the process of selecting and pricing perils presented to the insurer by potential clients. During this process, an employee with deep technical and conceptual understanding of the particular peril, the underwriter, establishes a distribution of the cash outflow the peril is expected to generate for the insurer. Sophisticated underwriting also resolves how adding a new peril to the existing risk pool of the insurer will impact the insurer’s overall performance. Based on such considerations, the underwriter then calculates a dollar price the customer should pay today for coverage. Depending on the compensation targets of the underwriter and the insurer’s pricing guidelines, the underwriter often adjusts the calculated price to reflect prevailing insurance market conditions. At the successful completion of the underwriting process, the customer (now the policyholder) pays the upfront price (or premium) and receives a legally binding promise by the insurer.

This promise obligates the insurer to pay specified damages that occur during a specified time if claimed by the policyholder, up to a specified limit and generally subject to a deductible. Thus, the insurer writes an American option on the terminal value of a real asset where the option’s exercise price is a random variable. Capital set aside by the insurer’s shareholders gives credibility that the insurer will honor the terms of this option. The insurer invests its capital and all associated money until it fulfills its obligations to the policyholder. Shareholders receive all the money left over. Thus, the possible sources for value to insurance shareholders are underwriting and investing.
Underwriting Operations

Hancock, Huber, and Koch (2001) as well as Babbel and Merrill (2005) provide a well-argued narrative of how underwriting operations, when competently executed, create value. In summary, the underlying driver of extracting value from underwriting is the willingness of policyholders to pay an economic rent for participation in an insurer’s risk pool. In a market with friction, policyholders pay such a rent because participation in the pool leaves their expected wealth unchanged while it decreases the volatility of their wealth (as in Gatzert and Schmeiser, 2012).

Even in frictionless markets, policyholders are still willing to pay a rent to participate in an insurer’s risk pool because insurance creates a hedge against other risks policyholders face. Quirin and Waters (1975), Fairley (1979), Hill (1979), and Kraus and Ross (1982) rely on the capital asset pricing model to derive an insurer’s competitive rate of return for underwriting. These authors examine the insurance contract as a hedge against systematic risk. Doherty and Schlesinger (1983) and Doherty and Garven (1986) examine the insurance contract as a hedge against the non-tradable background risk of the policyholder and rely on the option pricing model to derive an insurer’s competitive return from underwriting. These studies reach similar conclusions once one allows for differences in their assumptions about the direction of the correlation between the hedged cash flows. What determines the size of the rent policyholders are willing to pay is how losses from the insured peril are correlated with the cash flow policyholders wish to hedge. If large (small) claims coincide with states where policyholder wealth is low (high), the benefits of insurance to policyholders are more (less) valuable. Thus, when there is a negative or no correlation between the cash flow from an insurance contract and policyholder wealth, insurance provides a valuable hedge for the policyholder.

Insurers maintain their hold on their respective risk pools by protecting their private information on how each member of the pool actually performs, by sifting through data to better predict the likely performance of potential policyholders and by encouraging opacity on their risk classification processes, contract management, and actuarial modeling (Hancock et al., 2001; Babbel and Merrill, 2005; Cowley and Cummins, 2005). The empirical findings of Cummins, Dionne, Gagne, and Nouira (2009), Hu and McKitrick (2016), and others provide support for the underwriting-as-a-source-of-value narrative.

A less common argued source of value in underwriting operations is the ability of insurers to arbitrage. In the pre-1987 tax regime, Smith (1989) finds that property-liability insurers effectively could raise tax-free premiums that they then invested in tax-exempt securities. Under the existing tax regime, Petroni and Shackelford (1999) find that insurers that under-
write perils across states (such as those covered by a commercial multi-peril policy) allocate premiums to reduce their total state taxes. Also, insurers engage in jurisdictional arbitrage. Schlutter and Grundl (2012) find evidence of insurance holding firms transferring capital and operational risk across their individual insurance companies located in different regulatory jurisdictions.

The literature offers several alternative arguments to explain how underwriting generates value for a property-casualty insurer. There are no arguments to the contrary. Thus, the consensus in the literature supports the hypothesis that underwriting, in general, is a source of value for property-casualty insurers.

**Investing Operations**

Babbel and Merrill (2005, pp. 10 and 11) succinctly summarize the challenges a property-casualty insurer faces in generating value from its investing operations: “Insurers tend to hold a lot of publicly traded securities as assets. The extensive finance literature on market efficiency suggests that it is very, very difficult to create sustainable positive NPV [value] though investing in publicly traded securities. … Insurers also invest in illiquid assets such as real estate and private placement debt. Both of these are areas that have the possibility of rewarding sound analysis and shrewd investing. It is important to note, however, that … in both of these markets competition tends to drive excess profits … to zero.”

Empirical evidence supports this summary. For example, Alexander (2010) shows that the seemingly higher returns Berkshire Hathaway (an actively managed portfolio of firms, including insurers) earns are equivalent to that from the S&P500 in terms of return per unit of risk. Also, Becker and Ivashina (2015) find that those insurers that reach for yield in their fixed-income investments do so by taking on investment risk and do not generate superior risk-adjusted returns. Thus, better performing investing operations seem to trade risk for return, which is a value-neutral movement along the efficient frontier. In fact, Hancock et al. (2001) suggest that regulatory and rating agency restrictions, as well as a need for liquidity, constrain an insurer’s investments below the efficient frontier.

A potential argument for how insurers generate value from investing relies on the float underwriting operations generate. The use of float leverages the investing operations of property-casualty insurers. Such leveraging is assumed to create value because the cost of float is less than the cost of comparable-risk funds the insurer can raise in the market (Cummins and Lamm-Tennant, 1994; Staking and Babbel, 1995). This argument originates with Hofflander and Drandell (1969) and with Hammond et al. (1976), who show that an insurer with a positive underwriting return can earn a higher
investment return than a stand-alone investment trust of comparable risk. Hammond et al. (1976, p. 122) are explicit that the value an insurer can generate from their investing operations comes from using the insurer’s reserve account, which “stockholders hold no legal right to.” An analysis of Venter et al. (1998), however, suggests that the strength of the investment advantage reserves create is sensitive to how those reserves ultimately develop.

Unlike Hofflander and Drandell (1969) and Hammond et al. (1976), who use reported reserves at a point in time, Venter et al. (1998) use reserves as they develop over time for a cohort of policies. In analyzing a cohort of polices, Venter et al. (1998) indirectly control for under-reserving and for unexpectedly high losses. They find that whether the insurer’s investing operations outperform a stand-alone investment trust of comparable risk depends on whether claims paid to policyholders are earlier (later) or are larger (smaller) than anticipated when the reserve was originally invested and its asset composition decided on. Indeed, Fields and Venezian (1987) find that there is significant variation among insurers on the speed with which they pay claims out of their reserves. Furthermore, Petroni and Wahlen (1995) find that the stock price of property-liability insurers generally decreases as the book value of their loss reserves increases (which is contrary to what one should observe if investment proceeds generated from larger reserves create more value).

Another potential argument for how insurers generate value from investing relies on managing the duration gap between an insurer’s assets (which are mostly fixed-income securities) and its liabilities (which mostly are partially fixed, future payments to policyholders). Since the market values of both assets and liabilities of insurers are sensitive to movements in interest rates, whether a change in interest rates increases or decreases the value of an insurer is determined by the balance between duration of assets and of liabilities. As a general statement, for a property-casualty insurer, when interest rates increase (decrease), the market value of assets and the market value of liabilities decreases (increases) but by a different degree. If then an insurer allocates its invested assets in such a way so that their duration equals the duration of its liabilities—adjusting for the fact that insurers hold more assets than liabilities—the value of the insurer is unaffected by changes in interest rates (see for example Ahlgrim, D’Arcy, and Gorvett, 2004). Grove (1974) was the first to interpret the use of duration as a hedge for interest rate risk. Since the duration of an insurer’s liabilities is dictated by the rhythm of its underwriting operations, which in the short-term are fixed, the insurer can then allocate investment assets to either shorten or lengthen the duration of its investment portfolio. In this way an insurer can speculate on interest rate risk. Staking and Babbel (1995)
find that manipulating duration to take on extreme levels of interest rate risk increases the value of low-growth, property-casualty insurers as shareholders expropriate wealth from policyholders (but reduces the value of insurers with solid growth). Even then, however, there is difficulty in accurately establishing effective duration (as Babbel and Merrill, 2005, point out). Thus, even if the insurer speculates in the correct direction on interest rate movements, it still faces uncertainty in its measurement of duration, which then injects error in attempts to create value from a duration management strategy.

If an investment generates a commensurable return to its risk, then there is only a value-neutral movement along the efficient frontier. If, however, an investment generates less than a commensurable return, there is a dislocation from the efficient frontier and thus a decline in value. At best, the literature posits that the investing operations of insurers return no more than what is required to compensate for investment risk.

**RESULTS FROM SIMULATION MODELING**

The familiar *comparative statics* analysis identifies the direction of change of an endogenous variable in an equilibrium, in response to changes in an exogenous input variable. The analysis is *static* in that it does not consider a range of values in the exogenous variable or how the change flows from the exogenous variable to its equilibrium condition. By contrast, the study’s use of *simulation* allows analysis over a range of multiple input values and allows for interaction among those input values. The scope and granularity of the study’s use of simulation reflects design decisions intended to keep complexity manageable while still generating insights from its results. The purpose of the simulation is to aid the empirical analysis in this study. The simulation establishes the percent change in an insurer’s value associated with a percent change in its underwriting and investing performance. Such change reflects sequential increments of change in decision variables while all remaining decision variables are held constant.

The simplifying assumption governing the use of simulation for comparative analysis is that a movement in one decision variable does not affect other decision variables. This simulation uses additional simplifying assumptions. For example, the simulation does not allow for growth in premium or for the use of reinsurance or for competition in the supply of or the demand for insurance. While these and other such decisions are interrelated and impact the underlying profitability of an insurer, they are also extremely challenging to model (both conceptually and technically) in
the context of a market’s assumed equilibrium. Chiappori and Salanie (2008, p. 149) clearly summarize these challenges: “When modeling market equilibrium in an insurance context … the mere choice of an equilibrium concept is not clear. For instance, should equilibrium require nonnegative profit for each contract, or are cross subsidies allowed? Should one refer to equilibria à la Rothschild and Stiglitz, à la Wilson/Spence/Myazaki, à la Hellwig? And what should one do when the equilibrium fails to exist? From a theoretical perspective, the existence issue is especially difficult … because of its sheer complexity. Adverse selection is multidimensional (on risk and risk aversion), and the distribution of risk aversion at least is typically continuous. The various frictions introduced (finite elasticity, cost per contract and product, etc.) typically help generate existence of equilibrium; still, robust examples of nonexistence can be found.”

**Structure and Parametrization of the Simulation**

In the simulation, capital and premium are paid at the beginning of a period, claims and expenses are realized at the end of a period. Part of the realized claims and all of the realized expenses are paid out immediately. The remainder of the claims are paid in subsequent periods according to a fixed schedule. A separate reserve is set up for the funds needed to pay these remaining portions of the claims. Funds left over at the end of a period in excess of what capital is required to maintain a chosen probability of solvency are paid to shareholders. If the funds at the end of a period are less than what is required, shareholders infuse additional capital to the insurer. There are ten periods in the simulation. At the end of the last period the insurer terminates operations and runs off its reserve of realized claims that have not yet been paid. The data that parameterizes the simulation reflect the years used in the regression analysis of this study. Table 1 summarizes the parameters of the simulation.

At the beginning of a period, shareholders post an initial fixed amount of capital plus an additional amount so that total expected funds (capital, premium, and associated expected investment income) at the end of the period are sufficiently large to pay expected claims with a chosen probability level (as for example in Scordis, Barrese, and Yokohama, 2007, Footnote 5). This probability of solvency is arbitrarily set at a default quantity of 99 percent. This roughly corresponds to a credit rating of “good” to “very good” (Hamilton and Cantor, 2006). Premium at the beginning of a period is the discounted expected claims at the end of the period. In the simulation, an expense charge (or loading) proportional to expected claims allows the insurer to decide how much of the expected expenses to pass on to the policyholder. The loading proportion is arbitrarily set at a default quantity of zero.
Upon receipt of premium at the beginning of a period, the insurer sets up a separate reserve based on the expected claims at the end of the period (which the insurer then adjusts to reflect realized claims). The size of this reserve reflects that the insurer will pay 35 percent of the realized claims
immediately at the end of the period, and then at the end of each of the subsequent periods the insurer will pay 25 percent, 13, 9, 5, 4, 2, 1, 1, and 5 percent of the claim, respectively. These future portions of the claim payment are discounted at the risk-free rate of interest. This payout schedule reflects the insurance industry’s payment pattern as reported by a benchmark study (Plotting a Path in a Changing Market) the Guy Carpenter company issued in 2017. This Guy Carpenter study compiles data from 1,095 US insurers for the years 1989 to 2016. Thus, the implicit assumption in the simulation is that the payout pattern of claims is stable across time. Also, at the beginning of a period the insurer in the simulation invests all of its funds. For the funds allocated to the reserve, the insurer is only allowed the use of investment returns that are in excess of the discount rate of the reserve. In this way, adequate funds are assumed to compound within the reserve. The use of only the reserve’s excess investment funds reflects the idea that shareholders implicitly benefit from the investment income that reserves generate (Felblum and Thandi, 2003). If the investment return is less than the reserve’s discount rate, the insurer adds to the reserve from its available funds. In the simulation the default discount rate is 1.5 percent. Investment return is generated by the performance of an index which follows a Brownian motion. The mean and standard deviation of the index are 4 and 1.5 percent, respectively.

At the end of the period, the insurer faces stochastic claims and expenses. These claims and expenses are uncorrelated from period to period, but they are correlated to each other within a period. The stochastic claims for each period are generated from empirical distributions, which happen to be normal. The empirical distribution for realized claims has a minimum value of 65, a maximum value of 90, an expected value of 75, and a standard deviation of 6. The empirical distribution for expenses has a minimum value of 25, a maximum value of 28, an expected value of 27, and a standard deviation of 2. The rank-order correlation coefficient between claims and expenses is -0.07. The use of the rank-order coefficient is supported by Hofmann and Scordis (2018). The parameters of the index and of the empirical distributions reflect the reported experience of the US property-casualty industry for years 1998–2006 and through years 2013–2016. When claims are realized, the insurer uses the expected claims reserve it has set up at the beginning of the period to immediately pay 35 percent of these realized claims. The insurer then adjusts the expected claims reserve to reflect realized claims. If realized claims at the end of the period are less than expected claims, funds are transferred from the reserve to the insurer, otherwise the insurer provides funds to the reserve.

For example, if at the beginning of a period, the expectation is that at the end of of the period claims will be 75, the discounted reserve at the
period’s beginning is 71.9. At the end of the period this expected claims’ reserve generates a 3.2 percent return or investment income of 2.3. The insurer only uses 1.2 of the 2.3 investment income the reserve generates, with the remaining 1.1 accruing to the reserve. At the end of the period claims of 69.2 are realized. The insurer pays 35 percent (24.2) of the realized claims out of the expected claims’ reserve and adjust the remaining amount in the reserve to reflect the payment of the remaining realized claims. The discounted sum of these subsequent payments (17.3, 8.9, 6.2, 3.5, 2.8, 1.4, 0.7, 0.7, and 3.5) is 43.1 as compared to the discounted balance of the expected claims’ reserve of 46.7 (once the immediate payment of 24.2 is subtracted). Thus, for this example, funds of 3.6 are transferred from the reserve to the insurer. The reserve is adjusted similarly during each period to reflect the realization of claims as well as the payment of the portion of claims from past periods.

After the insurer pays claims and adjusts the reserve it pays all expenses. Thus, at the end of the period all funds that remain belong to the shareholders, unless the insurer has depleted its capital, in which case shareholders add capital as needed so that the insurer begins the next period with the appropriate probability of solvency. For each period the simulation calculates return to shareholders (net capital increase or decrease at the end of a period divided by capital at the beginning of the period), return from underwriting operations (claims and expenses divided by the compounded premium), and return from investing operations (investment income to shareholders divided by invested funds). The geometric averages from these respective returns are then the total return to shareholders (V), the total return from underwriting operations (UND), and the total return from investing operations (INV). The simulation repeats a large number of times under different sets of inputs (which Table 1 summarizes). In this way the simulation generates a combination of V, UND, and INV for each of the induced changes in its decision variables.

**Results**

A four-step process is followed to estimate the percent change in V for a percent change in UND \( \frac{\partial V}{\partial UND} \) and the percent change in V for a percent change in INV \( \frac{\partial V}{\partial INV} \) over a range of inputs: First, a decision variable (an input) in the model is changed by a small increment from its default quantity, while all other inputs are kept at their default quantity. Second, the model is iterated to produce 10,000 different combinations of V, UND, and INV. Third, for each set of these combinations I
estimate regression $V_i = \gamma_0 + \gamma_1 \text{UND}_i + \gamma_2 \text{INV}_i + \gamma_3 (\text{UND}_i \times \text{INV}_i) + \epsilon_i$ where subscript $i$ denotes simulated values from each of the model’s iterations. Then $\delta V/\delta \text{UND}$ is $(\gamma_1 + \text{INV})$ and $\delta V/\delta \text{INV}$ is $(\gamma_2 + \text{UND})$. Fourth, I repeat the first three steps for different incremental changes in the simulation’s inputs, compute $\left( \frac{\partial V}{\partial \text{UND}} \right)_V$ and $\left( \frac{\partial V}{\partial \text{INV}} \right)_V$, and plot them against each of their corresponding change in input. Figure 1 shows these percent changes. The solid line (–) represents the percent change in V for a percent change inUND at mean values of the data. The dashed line (−−) represents the percent change in V for a percent change in INV at mean values of the data (scaled by a factor of ten for ease of graphing).

Scenarios A, B, and C of Figure 1 relate to changes in the insurer’s underwriting operations. Scenario A permits only changes in the load percentage the insurer imposed on the expected claim (in increments of 3 percent from −6 to 21 percent). A negative (positive) loading depresses (elevates) premium at below (above) expected claims which implies that the insurer is selling coverage with a discount (surcharge). Scenario B permits only changes in the discount rate for reserves and premium (in increments of 0.5 percent from zero to 4.5 percent). The larger the discount rate the smaller the premium and the reserve for claims since they are discounted quantities of future cash flows. Scenario C permits only changes in the speed with which the insurer pays out its realized claims under the assumption that claims are all paid out in a single period. The period of payment ranges from the same period the claims are realized (duration of payment equals one) to ten periods after the claims are realized (duration of payment equals 10).

Scenarios D, E, and F in Figure 1 relate to changes in the insurer’s investing operations. Scenario D permits only changes in the mean return ($\mu$) of the index the insurer uses to invest its funds (in increments of 0.5 percent from 0.5 to 7 percent). Scenario E permits only changes in the volatility ($\sigma$) of the return of the index (in increments of 0.5 percent from 0.5 to 5 percent). Scenario F shows changes in the coefficient of variation (CV) of the index with change in CV induced by changing both volatility and mean at the same time. The change in CV in Scenario F is in increments of 0.5 units from a coefficient of 0.25 to 0.65.

In all scenarios, the simulated results show that V is more sensitive to a percent change in UND and comparatively less sensitive to a percent change in INV. The simulated results also suggest that a change in a decision variable, regardless whether the decision variable is associated with underwriting or with investing operations, impacts both the rate of change UND imparts on V as well as the rate of change of INV on V. For
example, as expected, Scenario B shows that as discount rates increase, a percent increase in the discount rate decreases the rate of increase in the relation between UND(INV) and V. One explanation of why a change in discount rate impacts both the rate of change of UND with respect to V and the rate of change on INV with respect to V is that an increase in the discount rate reduces both the premium and the reserve since they are discounted quantities of future cash flows. A smaller premium in relation to expected claims and expenses reduces the likelihood of an underwriting gain, while both a smaller premium and a smaller reserve reduce the
amount of investment income that can be generated and thus the contribution of investing operations to value.

For all scenarios except B and E, a percent increase in UND or INV is associated with a larger percent increase on V in the presence of larger input quantities. This suggests that a change in operating practices of aggressive insurers will have a larger impact on their value as compared to the same degree of change for insurers that operate less aggressively. Aggressive, in this content, is extracting premium in excess of expected claims, delaying payment of claims, and taking on more volatility in order to maintain a target investment return. Note, however, that Figure 1 shows only self-contained scenarios unconstrained from regulatory and market considerations. For example, while taking on investment risk, this simulation is consistent with the modeling results of Fischer and Schlutter (2015), as regulation prevents an actual insurer from investing all of its assets in volatile investments. Also, actual insurers operate under the influence of simultaneous changes in decision variables and are thus able to otherwise replicate the result of a decision that in itself is not encouraged by public policy. For example, increasing both mean investment return and its volatility (as in Scenario F) approximates the result from increasing the duration of the claims’ payment (Scenario C).

The results from the simulation suggest the likelihood of a moderating relation between underwriting operations and investing operations. The results from the simulation also suggest that it is unlikely to observe a difference in the empirical relation between underwriting performance and firm value across different time periods. It is likely, however, that there is an observed difference in the empirical relation between investing performance and firm value in periods characterized by low investment return and high volatility as compared to periods with low return and low volatility or high investment return and high volatility. The study, therefore, looks to its empirical results for further guidance.

RESULTS FROM REGRESSION ESTIMATORS

Data

The study continues with using regression to analyze how the operations of a property-casualty insurer contribute to its value. Thus, value, the dependent variable in the study, must be market-based. While there are many insurance operating companies that report accounting data to their respective regulators, these operating companies are bundled, many to a group, under the ownership of a holding firm. Several among these holding firms are either not publicly traded or do not report their financials in US
dollars. As a result, there is a relatively small population this study can draw data from. To enlarge the number of data points for analysis, I collect both cross-sectional and time-series observations in a panel data design.

There are periods, however, during which insurance firms as an industry were in a process of overhauling their operating architecture and periods of atypically hostile operating environment. A longitudinal study by Conning & Company (1997) concludes that property-casualty insurers by 1997 completed an overhaul of their operations to improve profitability. Thus, it can be argued that data before 1998 are not relevant to today. Collecting all periods since 1998, however, is also not suitable because there are extraordinary post-1998 periods that are likely to have significant influence on the relation between value and operating performance. For example, at the inception of the Great Recession, insurers experienced unprecedented losses in their investment portfolios, and since 2007 they have faced an uncharacteristically hostile investment environment. Then there are years 2011 and 2012, in which insurers experienced unusually large catastrophe claims across the US, rather than catastrophes confined to regions of the country. These two years include hurricanes Irene on the southeast coast, Isaac in the Gulf, and Sandy on the entire eastern seaboard, assorted tornadoes, winds, and ice storms in the midwest, and floods and wildfires in the west. Dealing with investment losses and claims from catastrophes is part of an insurer’s business. I posit, however, that such extraordinary events as the Great Recession and a national scope of catastrophes inject epistemic uncertainty in the relation between value and operating performance. The source of this uncertainty is the unknown success that insurance managers have in shaping market perceptions of the true impact such extraordinary events have on their firms.2

Thus, I select the study’s data to represent a typical operating environment for an insurer (to the extent that a representative operating environment exists). The information Table 2 compiles suggests that the environment following the Great Recession is not typical. Several years after the recession consumer confidence remained depressed and insurers reported weak underwriting and investing results. After the catastrophes of 2011/2012, consumer confidence strengthened and underwriting profitability improved, yet investing performance remained uncharacteristically weak.

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2For example, insurers exclude the impact of severe catastrophes from the underwriting performance they highlight to their investors. In the judgement of at least one insurance CEO (http://s1.q4cdn.com/677769242/files/doc_financials/2018/AGM/Chubb_Limited_2017_Anual_Report.pdf, page 6) doing so masks true performance since the reported underwriting performance includes all of the premium the insurer received from policyholders while ignoring extraordinary claims.
Nevertheless, since results from data with reference to today are likely to offer insights for the near-future of the industry, the study draws one of its data panels from the end of the second quarter of 2013 to the end of the last quarter of 2016.

The 2013 to 2016 data panel contains a total of 875 observations. It is unbalanced as several insurers announced their initial public offering within this period (e.g., 1347 Property Insurance Holdings on March 2015 or State National Company on November 2014). Even though at year-end 2016 there are 79 firms in the intersection of the CRSP and Compustat

### Table 2. Performance and Catastrophe Data at the End of Each Year

<table>
<thead>
<tr>
<th>Year</th>
<th>Consumer confidence index at year-end</th>
<th>Estimated claims from catastrophes ($ bil.)</th>
<th>Market risk premium (%)</th>
<th>3-year Treasury rate (%)</th>
<th>Industry net yield on investments (%)</th>
<th>Industry combined ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>98.2</td>
<td>21.0</td>
<td>13.2</td>
<td>1.5</td>
<td>3.04</td>
<td>100.0</td>
</tr>
<tr>
<td>2015</td>
<td>92.6</td>
<td>15.4</td>
<td>–0.2</td>
<td>1.3</td>
<td>3.18</td>
<td>97.3</td>
</tr>
<tr>
<td>2014</td>
<td>93.6</td>
<td>15.8</td>
<td>11.4</td>
<td>1.1</td>
<td>3.64</td>
<td>96.6</td>
</tr>
<tr>
<td>2013</td>
<td>82.5</td>
<td>13.4</td>
<td>35.2</td>
<td>0.8</td>
<td>3.43</td>
<td>95.2</td>
</tr>
<tr>
<td>2012</td>
<td>72.9</td>
<td>37.0</td>
<td>16.0</td>
<td>0.4</td>
<td>3.68</td>
<td>102.5</td>
</tr>
<tr>
<td>2011</td>
<td>69.9</td>
<td>36.2</td>
<td>1.0</td>
<td>0.4</td>
<td>3.83</td>
<td>107.7</td>
</tr>
<tr>
<td>2010</td>
<td>74.5</td>
<td>15.7</td>
<td>17.7</td>
<td>1.0</td>
<td>3.73</td>
<td>101.9</td>
</tr>
<tr>
<td>2009</td>
<td>72.5</td>
<td>11.8</td>
<td>29.1</td>
<td>1.7</td>
<td>3.93</td>
<td>100.0</td>
</tr>
<tr>
<td>2008</td>
<td>30.1</td>
<td>30.3</td>
<td>–38.4</td>
<td>1.0</td>
<td>4.20</td>
<td>104.6</td>
</tr>
<tr>
<td>2007</td>
<td>75.5</td>
<td>7.7</td>
<td>0.83</td>
<td>3.1</td>
<td>4.49</td>
<td>94.8</td>
</tr>
<tr>
<td>2006</td>
<td>91.7</td>
<td>10.8</td>
<td>10.6</td>
<td>4.7</td>
<td>4.50</td>
<td>91.6</td>
</tr>
<tr>
<td>2005</td>
<td>74.2</td>
<td>76.6</td>
<td>3.2</td>
<td>4.4</td>
<td>4.59</td>
<td>100.9</td>
</tr>
<tr>
<td>2004</td>
<td>97.1</td>
<td>35.2</td>
<td>10.7</td>
<td>3.3</td>
<td>4.03</td>
<td>98.4</td>
</tr>
<tr>
<td>2003</td>
<td>93.7</td>
<td>17.0</td>
<td>30.7</td>
<td>2.4</td>
<td>4.44</td>
<td>99.6</td>
</tr>
<tr>
<td>2002</td>
<td>86.7</td>
<td>7.9</td>
<td>–22.9</td>
<td>2.0</td>
<td>4.85</td>
<td>106.6</td>
</tr>
<tr>
<td>2001</td>
<td>88.4</td>
<td>36.3</td>
<td>–14.8</td>
<td>3.4</td>
<td>4.33‘</td>
<td>114.9</td>
</tr>
<tr>
<td>2000</td>
<td>98.4</td>
<td>6.4</td>
<td>–16.7</td>
<td>5.1</td>
<td>4.75‘</td>
<td>108.8</td>
</tr>
<tr>
<td>1999</td>
<td>105.4</td>
<td>12.1</td>
<td>20.2</td>
<td>6.3</td>
<td>5.04‘</td>
<td>106.7</td>
</tr>
<tr>
<td>1998</td>
<td>100.5</td>
<td>15.0</td>
<td>19.4</td>
<td>4.6</td>
<td>4.62‘</td>
<td>104.1</td>
</tr>
</tbody>
</table>

Source: Consumer confidence is from the Federal Reserve Economic archive (FRED), catastrophes are as reported by the Insurance Information Institute, the market risk premium is from the Fama-French Data Library, the Treasury rate is from the FRED archive, the net yield on investments is from the SNL Financial database where asterisks (*) indicate this study’s estimates, and the combined ratio is from A.M. Best’s Aggregates and Averages.
databases with NAICS code 524126 (direct property and casualty insurance carriers) or 524130 (reinsurers) this data panel consists of only 61 insurers since firms that, according to the information they report in Item 1 or Item 7 of their Form 10K, do not engage in underwriting property and casualty perils are eliminated.3

The study also uses a data panel from the first quarter of 1998 to the last quarter of 2006. Results from this data, as they may compare to the results from the 2013–2016 data, will provide insights for the analysis. While the unprecedented investment returns of the 2013–2016 data may prejudice the analysis of the relation between value and investing performance, the 1998–2016 data is characterized by ordinary investment returns. This 1998 to 2006 data panel consists of a total of 756 observations from 21 property-casualty insurers that have continued operations to year-end 2016. By including only firms that continued to operate through the 2013–2016 data panel I control for a string of high-profile acquisitions during the period.4 Since these 21 insurers are a subset of the firms in the 2013–2016 data, any difference in the results from the two data panels should be largely due to differences in the operating environment (as discussed in relation to Table 3b).

Measurement of Variables

Variables are from S&P’s Global Market Intelligence Data Platform. I measure value with Tobin’s Q (Q) as in Allayannis and Weston (2001), Hoyt and Liebenberg (2011), and Altuntas, Liebenberg, Watson, and Yildiz (2017), among others. This measure of value is attractive because it captures both current and future profitability. It also does not require an adjustment for risk. Under the assumption that a firm’s share price correctly reflects the present value of cash flows generated by its assets-in-place and the present value of cash flows from future growth opportunities, then Q in excess of one reflects the contribution to value of the firm’s growth opportunities. This is because investors, in anticipation of cash flows from growth, pay more for the firm than the residual value of its assets. The

3Some examples: Assured Guaranty and NMI Holdings provide financial guarantees for debt instruments. Assurant and Radian Group provide risk management services. Tiptree Financial and Citigroup are lenders and asset managers. Loews Corporation has no insurance operations except ownership in CNA Financial Corporation, which is included in the data. Donegal Group reinsurs all of its business with Donegal Mutual, with which it shares the same management, employees, and premises.

4Examples include the acquisition of Royal & Sun Alliance USA in 2006, the acquisition of PXRE Group, Ohio Casualty, TRW Inc. in 2007, the acquisition of Safeco in 2008, the acquisition of First Mercury Financial, PMA Capital in 2010.
calculation for Q, as in other studies, is the sum of the market value of the equity plus the book value of liabilities, divided by the book value of assets.

Seminal studies such as Allayannis and Weston (2001), Jin and Jorion (2006), and Hoyt and Liebenberg (2011), which also measure value as Tobin’s Q, all establish a positive relation between current profitability and Q. These studies measure current profitability as the accounting ratio return-on-assets, ROA. A challenge in my study is that ROA is itself a function of underwriting and investing performance. Since the study investigates how underwriting and investing performance impacts Q, I rely on a popular decomposition of ROA to factor ROA into underwriting and investing performance.

A popular decomposition of ROA is the product of return on revenue (ROR) multiplied by asset turnover (ATO):

\[
ROA = ROR \times ATO = \frac{\text{Net income}}{\text{Total revenue}} \times \frac{\text{Total revenue}}{\text{Total assets}}.
\]  

(1a)

I further decompose net income into net revenue from underwriting operations, net revenue from investing operations, and accrued expenses (such as those for administration, interest, taxes, amortization) so that:

\[
ROA = \left( \frac{\text{Net und. revenue} + \text{Net inv. revenue} + \text{Accruals}}{\text{Total revenue}} \right) \times \frac{\text{Total revenue}}{\text{Total assets}}
\]  

(1b)

which I simplify to:

\[
ROA = \left( \frac{\text{Net underwriting revenue}}{\text{Total assets}} \right) + \frac{\text{Net investing revenue}}{\text{Total assets}} + \frac{\text{Accruals}}{\text{Total assets}}.
\]  

(1c)

Thus, in place of ROA to measure current profitability, I use each of its components from Relation (1c). The ratio of underwriting revenue to assets is underwriting return on assets (UndROA) and the ratio investing revenue to assets is investing return on assets (InvROA).

I treat the ratio accruals to assets (AcA) as a control variable. Additional control variables are Growth (the percentage increase in shareholders’ capital from quarter to quarter), Liquidity (the ratio of cash and short-term (ST) investments to total assets), leverage, and size. I measure leverage as the ratio of liabilities to the market value of equity (LM) and alternatively as the ratio of liabilities to assets (LA). Size is the logarithm of the book value of assets.

Studies have also introduced numerous other variables as ad hoc controls. Examples are variables relating to corporate governance, institutional ownership, product, and geographic scope. Such control variables, however, do not consistently register as significant across studies (for
example Table 7, Model 1 in Jin and Jorion, 2006 or Table 5 Equation 1 in Hoyt and Liebenberg, 2011, or Table 4 in Altuntas et al., 2017). Perhaps this is because such ad hoc controls may influence value through current profitability and growth.

The resulting regression model is:

\[(Q)_{it} = \beta_0 + \beta_1(\text{UndROA})_{it} + \beta_2(\text{InvROA})_{it} + \beta(\text{Controls}) + \text{error}_{it}. \tag{2a}\]

While regression model 2a measures underwriting and investing performance in relation to assets, the insurance industry commonly measures underwriting performance by an insurer’s combined ratio (CR) and measures investing performance by the yield of invested assets (Yield). In regression model 2b I too use these measures of performance. To ease interpretation, I subtract an insurer’s combined ratio from one (1–CR) as a proxy for the insurer’s underwriting return. Yield is a proxy for the insurer’s investing return. Since I assume that variables 1–CR and Yield loosely capture ROR in equation 2a, I also include variable ATO from equation 2a as a control.

Thus, an alternative regression model is:

\[(Q)_{it} = \beta_0 + \beta_1(1–\text{CR})_{it} + \beta_2(\text{Yield})_{it} + \beta(\text{Controls}) + \text{error}_{it}. \tag{2b}\]

Tables 3a and 3b summarize each of the variables used to estimate the regression models 2a and 2b. The observed means of the variables in Tables 3a and 3b are statistically different except for that of variable ATO (p-value of 0.348). The fact that, on average, there is no difference in the ability of insurers to generate revenue from assets (ATO) between 2013–2016 and 1998–2006 is surprising, given the differences in the respective operating environments. The large maximum values for the variable Yield in each of the tables are associated with White Mountains and American International Group (AIG), respectively. White Mountains has been divesting subsidiaries at a substantial premium over their book value as part of a new competitive strategy. AIG reported the maximum Yield in the table in the first quarter of 2000. During this period AIG was reporting substantial gains from its Financial Products subsidiaries, which structured among other instruments credit-default swaps. At the end of year 2000, Financial Products contributed just under 30 percent of AIG’s investment income, according to the firm’s filings with the Securities and Exchange Commission (SEC). The maximum value for variable InvROA and the minimum value for variable AcA in Table 3b are associated with the Arch Capital Group in the first quarter of 1998. I am not able to explain these values for
Arch, except to point out that during this time Arch invested heavily in equities of other insurance firms. At the end of year 1998, 90 percent of Arch’s portfolio was entirely invested in stocks of other insurers or of companies providing services to the insurance industry, according to the firm’s filings with the SEC. The equity market in 1998 generated just under 15 percent return.

Table 3a also reports (quantities in parentheses) respective descriptive statistics for the 21 firms from years 2013–2016 that are also in the 1998–2006 data period. There are 351 such observations in years 2013–2016. The observed means of the variables in the 2013 to 2016 data period variables

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Median</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tobin’s Q</td>
<td>0.817</td>
<td>1.013</td>
<td>2.151</td>
<td>1.051</td>
<td>0.144</td>
</tr>
<tr>
<td>UndROA</td>
<td>-0.074</td>
<td>0.002</td>
<td>0.340</td>
<td>0.007</td>
<td>0.033</td>
</tr>
<tr>
<td>1–CR</td>
<td>-0.882</td>
<td>0.063</td>
<td>1.427</td>
<td>0.078</td>
<td>0.145</td>
</tr>
<tr>
<td>InvROA</td>
<td>-0.024</td>
<td>0.006</td>
<td>0.159</td>
<td>0.008</td>
<td>0.015</td>
</tr>
<tr>
<td>Yield</td>
<td>-0.143</td>
<td>0.033</td>
<td>0.254</td>
<td>0.032</td>
<td>0.023</td>
</tr>
<tr>
<td>AcA</td>
<td>-0.407</td>
<td>-0.001</td>
<td>0.097</td>
<td>-0.008</td>
<td>0.043</td>
</tr>
<tr>
<td>ATO</td>
<td>0</td>
<td>0.066</td>
<td>0.235</td>
<td>0.077</td>
<td>0.042</td>
</tr>
<tr>
<td>Growth</td>
<td>-0.186</td>
<td>0.013</td>
<td>1.096</td>
<td>0.019</td>
<td>0.083</td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.009</td>
<td>0.089</td>
<td>0.794</td>
<td>0.139</td>
<td>0.144</td>
</tr>
<tr>
<td>LM</td>
<td>0.133</td>
<td>2.185</td>
<td>19.652</td>
<td>2.778</td>
<td>0.144</td>
</tr>
<tr>
<td>LA</td>
<td>0.103</td>
<td>0.711</td>
<td>0.936</td>
<td>0.696</td>
<td>0.130</td>
</tr>
</tbody>
</table>

1Net underwriting revenue is the sum of policy income and fees less incurred losses, loss-adjustment expenses, and underwriting expenses.

2Net investing revenue is the sum of net income from investing and net realized capital gains.
are statistically different from those in the 1998 to 2006 period except for that of variables Growth, LM, and LA (p-value of 0.748, 0.783, and 0.709, respectively). It is reasonable that the same group of firms, which by 2016 have been operating for a long time, will have attained a stable growth rate and leverage. Unlike in Table 3a and Table 3b, where the mean of variable ATO is not statistically different between years 2013–2016 and years 1998–2006, variable ATO is different between these two periods for the 21 insurance firms that are in both data periods.
Thus, what should be impacting the statistical significance in testing the difference in means in ATO between 2013–2016 and 1998–2016 is the presence of the 40 relatively young firms that are included in 2013–2016 but not in 1998–2016. While the difference in the mean of ATO between these two periods is only 0.002, at the 95th percentile ATO is 0.161 for the 2013–2016 years and 0.184 for the 1998–2016 years. For reference, the 2013–2016 data period includes 40 insurers that are not in the 1998–2006 period for a total of 561 observations. The (mean, standard deviation) for each variable is as follows: Tobin’s Q (1.043, 0.142), UndROA (0.011, 0.039), 1–CR (0.092, 0.167), InvROA (0.009, 0.018), Yield (0.030, 0.026), AcA (−0.012, 0.054), ATO (0.082, 0.042), Growth (0.023, 0.096), Liquidity (0.155, 0.158), LM (2.447, 1.534), LA (2.447, 1.534), and Size (7.996, 1.916).  

Results  

In the data, there are observations that can be considered outliers, according to a plot of standardized residuals as well as the Belsley-Kuh-Welsch diagnostic. The dffits diagnostic, however, does not suggest the presence of any influential observations. The largest dffits value is 0.868 (Third Point Reinsurance for the third quarter of 2015). A Dickey-Fuller diagnostic (on variables Q, UndROA, InvROA, 1–CR, Yield) and an Engle-Granger diagnostic on the residuals from regression models 2a and 2b do not suggest the presence of unit-roots. Thus, I am confident that the data is suited to regression analysis and that regression results are not spurious. Mild multicollinearity is present in regression model 2a as a variance inflation factor (VIF) is greater than 30. Despite the presence of mild multicollinearity, however, estimated coefficients are still statistically significant. Multicollinearity does not appear to be an issue in regression model 2b. All of the variance inflation factors (VIF) are considerably below ten.

It is possible that insurers pass on some of the impact of systematic factors such as that from natural catastrophes to their policyholders, as the empirical results of Hagendorff, Hagendorff, and Keasey (2015) suggest. Nevertheless, I control for the impact of time by estimating the study’s regression models using fixed effects under the assumption that events embedded in time impact similarly each observation in the data. I estimate a robust fixed effects model using the estimator of Davidson-MacKinnon for unspecified heteroscedasticity in fixed effects, the counterpart of the

5Note that re-estimating the relations in Table 7 using only the 351 observations from years 2013–2016 that are also in the 1998–2006 data period, or only the 561 that are not in the 1998–2006 period (available upon request), does not alter the conclusions of the study. The true effect in the data is still positive for variable 1–CR and negative for variable Yield/GOV.
White estimator for ordinary least squares estimation. There is no difference in results with and without a Newey-West correction for autocorrelation. The alternative assumption to fixed effects is that time impacts randomly each observation in the data. Large values in a Hausman specification test, however, suggest in favor of the fixed effects estimator. Under the fixed effects estimator, the classical constant term \( \beta_0 \) from regression models 2a and 2b is instead \( \alpha_1 \gamma_1 + \alpha_2 \gamma_2 + \ldots + \alpha_N \gamma_N \) where each alpha is a firm-specific constant and each gamma is a time-specific dummy variable.

Tables 4a and 4b report results from estimating regression models 2a and 2b for the 2013–2016 and 2013–2016 data set, respectively. Underwriting performance is positively related to value in both of the data panels. The p-values associated with the estimated coefficients of variables UndROA and 1–CR suggest a confidence level exceeding 99 percent and the respective confidence intervals suggest that the strength of the relation between underwriting performance and value is a true effect in the data. In Table 4a (the 2013–2016 data) \( \delta Q/\delta \text{UndROA} \) is 3.048 and \( \delta Q/\delta (1–CR) \) is 0.098. In Table 4b (the 1998–2006 data) \( \delta Q/\delta \text{UndROA} \) is 3.042 and \( \delta Q/\delta (1–CR) \) is 0.036.

Unlike underwriting performance, the relation between investing performance and value in Tables 4a and 4b appears to be data specific. In the 2013 to 2016 data, investing performance is negatively related to value: \( \delta Q/\delta \text{InvROA} \) is –1.209 but at a confidence level of 86 percent. In the 1998 to 2006 data, investing performance is negatively related to value: \( \delta Q/\delta \text{InvROA} \) is 2.950 at a confidence level of over 99 percent. For the 2013–2016 data \( \delta Q/\delta \text{Yield} \) is –0.661 at a confidence level of over 99 percent, and for the 1998–2006 data it is 0.395 at a confidence level of over 95 percent. Their respective confidence intervals, however, suggest that the coefficients may not be reflecting a true effect in the data population. Two of the confidence intervals straddle zero and the lower bound of one is zero (at two decimal places). Also, note the wide range of the confidence interval for the estimated confidence that corresponds to \( \delta Q/\delta \text{InvROA} \) for the 1998 to 2006 data relative to that for the 2013 to 2016 data. The wider the range the more uncertainty there is about a coefficient estimating a true effect in the data.

The study continues its investigation with regression model 2b because the confidence intervals associated with variables 1–CR and Yield are quite narrow as compared with the confidence intervals associated with variables UndROA and InvROA (in model 2a). Narrower confidence intervals indicate less uncertainty in the ability of a regression to estimate the size of any true effect in the data. I re-estimate regression model 2b with the added interaction term (1–CR \( \times \) Yield). The use of this interaction term
recognizes insights from Figure 1 that changes in underwriting and investing performance concurrently influence value.

The introduction of the multiplicative interaction term \((1 – CR \times Yield)\) in model 2b requires the calculation of conditional coefficients for variables \(1 – CR\) and \(Yield\). The calculation of conditional coefficients accounts for the joint influence on \(Q\) of both underwriting and investing performance. For example, consider regression model 2b which is now \(Q_{it} = \beta_0 + \beta_1(1–CR)_{it}\)
\[ + \beta_2 (Yield)_{it} + \beta_3 (1-CR \times Yield)_{it} + \ldots \] Its estimated coefficient \( \hat{\beta}_1 \) represents the main effect for underwriting performance. Its estimated coefficient \( \hat{\beta}_3 \) is the moderating effect of investing performance on underwriting performance. The conditional coefficient of \( 1-CR \) (\( \hat{\beta}_1 \)) at the mean value of the data is then:

\[
\hat{\beta}_1 = \frac{\delta(Q)}{\delta(1-CR)} = \hat{\beta}_1 + \hat{\beta}_3 Yield
\]  

(3a)
and its corresponding conditional standard error is:

$$s(\beta_1 \text{ at } \overline{\text{Yield}}) = \left[ \sigma^2(\hat{\beta}_1) + (\text{Yield})^2 \sigma^2(\hat{\beta}_3) + 2 \text{Yield} \text{Cov}(\hat{\beta}_1; \hat{\beta}_3) \right]^{1/2} \quad (3b)$$

where Cov(.) is the covariance operator with (3a) and (3b) then used to construct the relevant tests of significance.

Table 5 shows results from regression model 2b with the inclusion of the multiplicative interaction term (1−CR × Yield). The use of the interaction variable introduces multicollinearity as indicated by variance inflation factors for both 1−CR and the interaction term that are near 10. However, results from Table 5 regarding the influence of underwriting and investing on value suggest the absence of an interaction effect. The estimated coefficients of the interaction effect variable are not significantly different from zero. Furthermore, from Table 5 where the interaction term is present, at mean values of the data a one percent change in 1−CR or a one percent change in Yield changes Q by the same percent (to two decimal places) as it does without the interaction term in Tables 4a and 4b.

So far, the results from the regression analysis, taken together, suggest that underwriting performance increases value regardless of the data. However, whether investing performance increases or decreases value depends on the time of the data. The relation between investing performance and value is negative for the 2013–2016 data and positive for the 1998–2006 data. I explore further the relation between investing and value by estimating model 2b with two separate sub-samples of the current data. I report results from these sub-samples in Table 6.

In Table 6, sub-sample A represents observations for an insurer that experienced both poor underwriting (1−CR < 0) and aggressive investing (Yield > Median yield of the data) during a quarter in the data. Sub-sample B represents observations with strong underwriting (1−CR > 0) and conservative investing (Yield < Median yield of the data). For the 2013–2016 data there are 102 observations in sub-sample A and 389 in B. For the 1998–2006 data there are 193 observations in sub-sample A and 303 in B. The results in Table 6, for the most part, suggest that profitable underwriting increases value while unprofitable underwriting reduces value. However, in the context of Table 6, aggressive investing (earning above the data’s median yield) is not associated with increased value nor is conservative investing (earning below the data’s median yield) associated with decreased value. Instead, for the 2013–2016 data the estimated coefficients for Yield are both no different than zero and for the 1998–2006 data the estimated coefficients for Yield are both negative. Yet, in Table 4a the estimated coefficient of Yield
Table 5. Underwriting and Investing Interaction, Model 2b

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient (p-value)</td>
<td>Confidence interval (95 percent)</td>
<td>Coefficient (p-value)</td>
<td>Confidence interval (95 percent)</td>
</tr>
<tr>
<td>1–CR</td>
<td>0.064 (0.131)</td>
<td>−0.019 0.147</td>
<td>−0.004 (0.937)</td>
<td>−0.091 0.084</td>
</tr>
<tr>
<td>Yield</td>
<td>−0.793 (0.000)</td>
<td>−1.207 −0.379</td>
<td>0.416 (0.044)</td>
<td>0.012 0.820</td>
</tr>
<tr>
<td>1–CR × YieldAcA</td>
<td>1.346 (0.202)</td>
<td>−0.721 3.414</td>
<td>0.522 (0.322)</td>
<td>−0.512 1.556</td>
</tr>
<tr>
<td>ATO</td>
<td>1.361 (0.000)</td>
<td>1.131 1.590</td>
<td>2.229 (0.000)</td>
<td>1.604 2.854</td>
</tr>
<tr>
<td>Growth</td>
<td>0.282 (0.000)</td>
<td>0.184 0.381</td>
<td>−0.018 (0.642)</td>
<td>−0.092 0.057</td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.018 (0.619)</td>
<td>−0.054 0.091</td>
<td>0.726 (0.496)</td>
<td>−1.361 2.812</td>
</tr>
<tr>
<td>LA</td>
<td>0.275 (0.000)</td>
<td>0.183 0.367</td>
<td>0.473 (0.655)</td>
<td>−1.605 2.552</td>
</tr>
<tr>
<td>Size</td>
<td>−0.002 (0.459)</td>
<td>−0.008 0.004</td>
<td>0.019 (0.009)</td>
<td>0.005 0.033</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>30.8%</td>
<td></td>
<td>61.9%</td>
<td></td>
</tr>
<tr>
<td>F-test</td>
<td>18.7 (0.000)</td>
<td></td>
<td>29.5 (0.000)</td>
<td></td>
</tr>
</tbody>
</table>

Conditional coefficients:

<table>
<thead>
<tr>
<th></th>
<th>Coefficient (p-value)</th>
<th>Confidence interval (95 percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–CR</td>
<td>0.107 (0.002)</td>
<td>0.041 0.173</td>
</tr>
<tr>
<td>Yield</td>
<td>−0.688 (0.000)</td>
<td>−1.051 −0.325</td>
</tr>
</tbody>
</table>

Note: ✓ denotes an estimated coefficient for which both its p-value and confidence interval suggest that its size represents a true effect in the data.

is negative for the 2013–2016 data and in Table 4b it is positive for the 1998–2006 data.

One explanation for the results in Table 6 is that since each sub-sample selects on the basis of individual quarterly observations, such observations may be outliers for a particular firm. The results in Table 6, however, in conjunction with the results in Tables 4a and 4b, point to a key difference between the 2013–2016 and 1998–2006 data. What makes the two periods of analysis different (since the firms in the one data panel are a subset of
the other data panel) is the yield on the benchmark risk-free bonds. For example, the 3-year Government Bond yields on average 0.981 percent during the 2013–2016 data as compared to 4.14 percent during the 1998–2006 data. Since the mean for variable Yield (from Tables 2a and 2b) is 3.19 percent for the 2013–2016 period and 5.35 percent for the 1998–2006 period—and insurers hold their assets in mostly fixed-income securities—

\(^6\)Selecting sub-samples on the basis of two consecutive observations still results in estimated coefficient signs as in Table 6. However, sub-samples contain fewer observations. For example, for the current data sub-sample A drops to 66 observations and sub-sample B drops to 321 observations.
during the 2013–2016 period to achieve yield insurers have to take on more risk as compared to insurers during the 1998–2006 period.7

To control for differences in the benchmark risk-free rate, I re-estimate regression model 2b once I scale variable Yield by the yield on the Government Bond at the end of the corresponding quarter of each observation.8 I denote this scaled variable as Yield/Gov. Indeed, a comparison of variable Yield/Gov across the study’s two data sets suggests that if in fact risk and return relate linearly as generally believed, the average insurer in the 2013–2016 data takes on more risk to generate less return than the average insurer in the 1998–2006 data. The mean of variable Yield/Gov in the 2013–2016 data is 3.494 as compared to 1.425 in the 1998–2006 data. In this estimation (whose results are available upon request), δQ/δ(Yield/Gov) is negative for the 2013–2016 period where taking on a risk appears to generate relatively low return. By comparison, for the 1998–2006 period, where taking on risk appears to generate more return, δQ/δ(Yield/Gov) is not significantly different from zero. These results fit well the narrative that there is no increase in value if taking on more risk generates a commensurable increase in return, but there is a decrease in value if taking on more investment risk results in less than a commensurable increase in return.

It is noteworthy that in all regression results the estimated coefficient of variable ATO is consistently positive. I am not able to establish a full mediating relation through variable ATO to value, as in Baron and Kenny (1986). However, variable ATO seems to moderate the relation to value as the results in Table 7 suggest. Table 7 reports on results from estimating the regression model 2b with variable Yield/Gov in place of variable Yield.

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7At year-end 2016, property-casualty insurers in the US held 67.6 percent of their assets in fixed-income securities and 19.1 percent in equities.

8There is not a clear way of measuring the overall net investing risk of publicly traded insurers, which is what this study uses. Unlike individual, US-based insurance operating companies that report granular data to the National Association of Insurance Commissioners (NAIC), their publicly-traded parents do not report such data for their consolidated operations. It is not possible to deduce the investment risk of all publicly traded insurers by aggregating the data they report to the NAIC because many of them also have substantial operations outside the US. Publicly traded insurers do report consolidated data of the entire scope of their operations to the SEC, but the data they report to the SEC only discloses broad asset categories of investments and provides some indication (which can be either quantitative or qualitative) of the investments’ net market risk. Even then, such information is not identical across insurers, or over time for the same insurer. Given the publicly available data, and the literature on the different ways to quantify investing risk, I cannot identify a more precise way to measure the net risk of an insurer’s consolidated investing operations beyond the Yield/Gov ratio I use. Note that Becker and Ivashina (2015), despite the broad title of their paper, only investigate the risk-yield relation of the fixed-income securities individual US-based insurance operating companies report to the NAIC.
Table 7. Scale Variable \( \text{Yield} \) by the Yield on the Government Bond (\( \text{Yield/Gov} \)) and include interactions with variable \( \text{ATO} \)

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Confidence interval</td>
<td>Coefficient</td>
<td>Confidence interval</td>
</tr>
<tr>
<td></td>
<td>(p-value)</td>
<td>(95 percent)</td>
<td>(p-value)</td>
<td>(95 percent)</td>
</tr>
<tr>
<td>( 1-\text{CR} )</td>
<td>-0.321</td>
<td>-0.429 –0.213</td>
<td>-0.279</td>
<td>-0.368 –0.185</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>( \text{Yield/Gov} )</td>
<td>-0.000</td>
<td>-0.006 0.005</td>
<td>0.011</td>
<td>-0.013 0.034</td>
</tr>
<tr>
<td></td>
<td>(0.924)</td>
<td></td>
<td>(0.372)</td>
<td></td>
</tr>
<tr>
<td>( \text{ATO} )</td>
<td>1.349</td>
<td>1.047 1.651</td>
<td>3.211</td>
<td>2.728 3.693</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>( 1-\text{CR} \times \text{ATO} )</td>
<td>6.449</td>
<td>5.096 7.802</td>
<td>8.387</td>
<td>6.447 10.327</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>( \text{Yield/Gov} \times \text{ATO} )</td>
<td>-0.088</td>
<td>-0.150 –0.026</td>
<td>-0.329</td>
<td>-0.624 –0.034</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td></td>
<td>(0.290)</td>
<td></td>
</tr>
<tr>
<td>( \text{Growth} )</td>
<td>0.189</td>
<td>0.094 0.284</td>
<td>-0.065</td>
<td>-0.157 0.028</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.170)</td>
<td></td>
</tr>
<tr>
<td>( \text{Liquidity} )</td>
<td>0.044</td>
<td>-0.025 0.113</td>
<td>2.141</td>
<td>-0.131 4.413</td>
</tr>
<tr>
<td></td>
<td>(0.211)</td>
<td></td>
<td>(0.062)</td>
<td></td>
</tr>
<tr>
<td>( \text{LA} )</td>
<td>0.252</td>
<td>0.165 0.339</td>
<td>2.184</td>
<td>-0.110 4.478</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.065)</td>
<td></td>
</tr>
<tr>
<td>( \text{Size} )</td>
<td>-0.005</td>
<td>-0.010 0.001</td>
<td>0.035</td>
<td>0.027 0.041</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>( \text{Adjusted } R^2 )</td>
<td>38.2%</td>
<td></td>
<td>54.7%</td>
<td></td>
</tr>
<tr>
<td>( \text{F-test} )</td>
<td>24.6 (0.000)</td>
<td></td>
<td>21.8 (0.000)</td>
<td></td>
</tr>
<tr>
<td>( \text{Conditional coefficients:} )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( 1-\text{CR} )</td>
<td>0.177</td>
<td>-0.013 0.062</td>
<td>0.356</td>
<td>0.279 0.433</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>( \text{Yield/Gov} )</td>
<td>-0.007</td>
<td>-0.009 –0.004</td>
<td>-0.014</td>
<td>-0.029 0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.058)</td>
<td></td>
</tr>
<tr>
<td>( \text{ATO} )</td>
<td>1.545</td>
<td>1.323 1.767</td>
<td>2.620</td>
<td>2.324 2.916</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
</tbody>
</table>

Note: ✓ denotes an estimated coefficient for which both its p-value and confidence interval suggest that its size represents a true effect in the data.
and the inclusion of the multiplicative interaction terms \((1-CR \times ATO)\) and \((Yield/Gov \times ATO)\).

Table 7, for the 2013–2016 data, shows both interaction variables \((1-CR \times ATO)\) and \((Yield/Gov \times ATO)\) to be significant, but with opposing signs. The estimated coefficient of \((1-CR \times ATO)\) is positive. That of \((Yield/Gov \times ATO)\) is negative. This suggests that the more positive \(ATO\) is, the more positive is the effect of \(1-CR\) on \(Q\). Conversely, the more positive \(ATO\) is, the more negative is the effect of variable \(Yield/Gov\) on \(Q\). The statistical significance (with a negative sign) of \(1-CR\) in the presence of a significant interaction variable merely implies that underwriting performance has a negative effect on value when \(Yield/Gov\) equals zero. Similarly, the fact that \(Yield/Gov\) is not significant implies that relative investing performance does not have an effect on value when \(1-CR\) equals zero, even though it does have an effect for other values of \(1-CR\). It is precisely because of such an effect that interaction \((Yield/Gov \times ATO)\) is significant.

In Table 7, for the 2013–2016 data the conditional coefficient \(\delta Q/\delta(1-CR)\) is 0.177 and the conditional coefficient \(\delta Q/\delta(ATO)\) is 1.545. While the p-value of the conditional coefficient \(\delta Q/\delta(Yield/Gov)\) indicates statistical significance, the upper bound of its corresponding confidence interval is zero (at two decimal places). For the 1998–2006 data the conditional coefficient \(\delta Q/\delta(1-CR)\) is 0.356 and the conditional coefficient \(\delta Q/\delta(ATO)\) is 2.620. Similarly, the p-values of the conditional coefficient \(\delta Q/\delta(Yield/Gov)\) indicate statistical significance but the upper bound of its corresponding confidence interval is zero (to three decimal places). Respectively, \(\delta Q/\delta(Yield/Gov)\) is \(-0.007\) and \(-0.014\). At mean data values, for both data periods a one percent change in \((Yield/Gov)\) changes \(Q\) by the same percentage (to two decimal places) as the change in Tables 4a, 4b, 5, and 7.

**CONCLUSION AND IMPLICATION**

This study investigates the relation of underwriting and investing operations to the value of a property-casualty insurer. The investigation relies on both simulation and analysis of data from two panels. One data panel is characterized by an environment of underwriting gains and a challenging investment environment. The other data panel is characterized by an operating environment of both underwriting gains and losses in conjunction with a favorable investment environment. The study finds a positive relation between underwriting performance and value. The relation between investing performance and value appears to be specific to the investment environment. The empirical relation between investing performance and value is negative for the 2013–2016 data and positive for the
1998–2006 data. However, when investing performance is adjusted for risk it turns negative for the 2013–2016 data and non-significant for the 1998–2006 data.

The positive relation between underwriting performance and value can be explained by insurers possessing a comparative informational advantage in underwriting. Hancock et al. (2001), Doherty and Schlesinger (1983), and Gatzert and Schmeiser (2012) among others, identify such advantages from underwriting. The findings on the relation between investing performance and value are consistent with the empirical findings of Alexander (2010) and of Becker and Ivashina (2015). The relation between investing performance and value is consistent with the view that if taking on more risk produces a commensurable increase in return there is only a value-neutral movement along the efficient frontier, but when taking on risk results in less than a commensurable increase in return there is a dislocation from the efficient frontier. The empirical results of this study are also consistent with the major conclusion of Froot and Stein (1998) that a financial firm should not be exposed to financial risk (their Proposition 1 and 2) if the firm’s goal is to maximize the value of shareholders. Thus, for an insurance firm, the Froot and Stein (1998) result implies that it is underwriting that creates value, not exposure to financial risk. This is indeed the conclusion of this empirical study.

In the course of analysis, the study also finds a positive relation between asset turnover and value, and that as asset turnover increases it amplifies the positive effect of underwriting performance on value. This amplifying effect does require functioning investing operations. There is little in the literature on how (or why) an insurer’s ability to generate revenue impacts its value. Thus, this can be the subject of future research. Jegadeesh and Livnat (2006) as well as Chandra and Ro (2008) find that a firm’s ability to generate revenue conveys positive information to the market not contained in its net earnings. Chandra and Ro (2008) further conclude that the role of revenue in a firm’s valuation is heightened when earnings are extreme. Extreme earnings in property-casualty insurance operations are not unusual given the sensitivity of earnings to natural catastrophes.

The study’s results, that the enduring source of value for an insurer is underwriting, have implications for the strategic direction of insurers. Property-casualty insurers generate value from underwriting because they operate as risk warehouses rather than as risk intermediaries. A risk warehouse, according to Cowley and Cummins (2005), originates risk financing products and retains their expected claims on its books. By comparison, a risk intermediary repackages, instead of retaining, expected claims for sale to investors in the form of securities. To prosper, a risk
warehouse needs to have an advantage in extracting information from data and using such information to improve the pricing (and design) of its products (Gogol, 1993; Cowley and Cummins, 2005; Froot, 2007).

The information advantage of risk warehouses, however, is under threat from advances in the collection and analysis of data. Formally Cather (2018) and colloquially Scordis (2016) explain that since the expense of finely classifying consumers according to their potential cost to the seller of risk financing products is shrinking, those firms that can access better data and harvest it for the information it contains can poach all the lower-cost consumers from rivals by offering slightly better terms. Such a move will then force rivals to defend their share of consumers by quickly adopting advances in information analysis. Thus, “one should expect that cost-effective pricing innovations will be rapidly adopted cross insurers often at speeds so fast that regulators cannot keep pace” (Cather, 2018, p. 359).

At the limit of the data-driven economy, however, the informational advantage in classifying risks shifts not just among risk warehouses but from risk warehouses to the technology platforms that generate the actual data on consumers. Cather (2018) demonstrates how data-driven innovations in risk-classification can abruptly disturb property-casualty insurance markets. The findings of this study—that insurers generate value consistently from their underwriting operations (rather than from their investing operations)—underscores the need for a value proposition for insurers that is resilient to an environment saturated by data-intensive pricing algorithms.

REFERENCES


