RISK TAKING AND RISK MANAGEMENT OF INSURANCE COMPANIES: EFFECTS OF LOCAL RELIGIOUS BELIEFS AND ENTERPRISE RISK MANAGEMENT ADOPTION

by

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(Under the Direction of Thomas R. Berry-Stölzle)

ABSTRACT

In my dissertation, I study risk-taking and risk management of insurance companies, by examining the effects of local religious beliefs on insurers' risk-taking behaviors and the effects of Enterprise Risk Management (ERM) adoption on insurers' cost of capital. My dissertation consists of two essays. In the first essay, I investigate whether the adoption of the ERM approach affects companies' cost of equity capital. ERM is a process that manages all risks in an integrated, holistic fashion by controlling and coordinating offsetting risks across the enterprise. I restrict my analysis to the U.S. insurance industry to control for unobservable differences in business models and risk exposures across industries. I simultaneously model companies' adoption of ERM and the effect of ERM on the cost of capital. I find that ERM adoption significantly reduces company's cost of capital. My results suggest that cost of capital benefits are one answer to the question how ERM can create value. In the second essay of my dissertation, I empirically examine the effect of local religious beliefs measured by the fraction of Catholics (or the fraction of Protestants) living in a certain geographic region on risk-taking behaviors of life insurers headquartered in that region. I find that annuity writers, more risky than life writers, are more common in high Catholic ratio or low Protestant ratio areas. Further, I employ three risk measures—asset risk, investment risk, and total risk—to proxy for life insurers' risk-taking activities. I find that life insurance companies located in high Catholic-to-Protestant ratio, high Catholic ratio, or low Protestant ratio areas assume significantly more risk. Corporate risk-taking behaviors in the financial services sector has received increased attention from policymakers and regulators in the aftermath of the recent financial crisis, and my research contributes to the currently ongoing public policy discussion.

INDEX WORDS: Insurer Risk-taking, Local Religious Beliefs, Enterprise Risk Management, Implied Cost of Capital

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DEDICATION

To My Parents

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ESSAY ONE:

ENTERPRISE RISK MANAGEMENT

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1. Introduction

Enterprise Risk Management (ERM) is a holistic approach to risk management. Traditionally, corporations managed risks arising from their business units separately in each unit. ERM improves on this traditional “silo” based approach by coordinating and controlling offsetting risks across the enterprise. A number of surveys document how firms implement ERM programs to achieve such synergies between different risk management activities (see, e.g., Colquitt, Hoyt, and Lee, 1999; Kleffner, Lee and McGannon, 2003; Beasley, Clune and Hermanson, 2005; Altuntas, Berry-Stölzle, and Hoyt, 2011), a number of studies on firms’ decision to start an ERM program provide evidence that firms adopt ERM for direct economic benefits (see, e.g., Liebenberg and Hoyt, 2003; Pagach and Warr, 2011), and a limited number of studies provide evidence that ERM is associated with improvements in firm performance and increases in firm value (see, e.g., Grace et al., 2013; Hoyt and Liebenberg, 2011; Eckles, Hoyt, and Miller, 2014). While this prior literature argues that ERM can create value by creating synergies between different risk management activities, increasing capital efficiency, avoiding the underinvestment problem in financially constrained firms, and by reducing the cost of external financing, there is a lack of empirical evidence supporting these claims.

The goal of my research is to shed some light on the fundamental question *how* ERM can create value. I specifically focus on the relationship between ERM adoption and firms’ cost of external financing, and investigate whether ERM adoption is negatively associated with the cost of equity capital. Such a research design allows me to evaluate whether cost of capital benefits are one mechanism for value creation by the ERM approach. In addition, such a research design provides evidence on whether stockholders of firms view ERM as a beneficial and value enhancing activity or not.

To avoid possible spurious correlations caused by unobservable differences in business models and risk exposures across industries, I restrict my analysis to a single industry that is almost tailor-made for an empirical analysis of ERM programs and their cost of capital implications: the U.S. insurance industry. The insurance industry embraced the ERM approach, and a substantial fraction of insurers adopted an ERM program, providing the necessary variation for an empirical analysis. In addition, the U.S. insurance industry is the only insurance industry worldwide with a substantial number of publicly traded stock companies, providing the necessary stock price data for cost of equity capital calculations.

My cost of capital measure is based on the Gebhardt, Lee and Swaminathan (2001) implied cost of capital model, which equates the firm's market value of equity with its discounted future cash flow estimates, and solves for the required internal rate of return. I use an implied cost of capital measure because such measures better explain variations in expected stock returns than realized stock returns (see, e.g., Gebhardt, Lee and Swaminathan, 2001; Pástor, Sinha, and Swaminathan, 2008). Following the procedure suggested by Beasly, Pagach, and Warr (2008), Hoyt and Liebenberg (2011), and Pagach and Warr (2011), I systematically search newswires and other media, as well as financial reports, for evidence of ERM program adoption by my sample insurance companies. I then use two procedures to test whether ERM adoption is actually accompanied by a decrease in firms' cost of capital. First, I use an event study methodology in the broad sense, and test for an abnormal reduction in the cost of capital around the year of ERM adoption. Second, I explicitly model the determinants of ERM program adoption and estimate a two-equation treatment effects model to assess the effect of ERM use on firms' cost of capital. For ERM adopters, the ERM indicator variable in this model is coded equal to one in the year of ERM adoption and all following years; the variable is equal to zero in the years prior to ERM adoption. For firms that do not adopt ERM during my sample period, the ERM indicator is equal to zero for all firm-year observations.

In both the "event study" as well as the treatment effects model, I find that ERM adoption is significantly associated with a reduction in firms' cost of equity capital. Overall, my results suggest that cost of capital benefits are one answer to the question how ERM can create value.

My treatment effects model results indicate that on average ERM adoption decreases firms' cost of equity capital by approximately 180 basis points.[1] In the Gordon (1959) growth model, under a zero dividend growth assumption, a 180 basis points reduction in cost of capital translates into a 15.697% increase in firm value. This is comparable to the ERM value premium of approximately 20% documented in Hoyt and Liebenberg (2011).

The paper proceeds as follows. In the next section, I discuss related literature and the conceptual background of my research design. This is followed by a description of the data and methodology used, and a section containing the results. The final section concludes.

2. Literature and Conceptual Background

2.1 ERM Literature

The literature on ERM follows three main themes. The first strand of literature is mainly descriptive and focuses on the question how firms implement ERM programs in practice (see, e.g., Colquitt, Hoyt, and Lee, 1999; Kleffner, Lee and McGannon, 2003; Beasley, Clune and

[1] The 1.8% reduction in ICC by ERM adoption seems to be substantially larger than the other effects documented in the literature. Hail and Leuz (2009) examine whether cross-listing in the U.S. decreases firms' costs of capital. They find firms with cross-listings on U.S. exchanges experience a reduction in their cost of capital between 0.7% and 1.2%. In other words, the effect of a cross-listing on a firm's cost of capital is about half the size of the effect of ERM adoption. Ashbaugh-Skaife et al. (2009) investigate the effects of management evaluation and independent audits of internal control effectiveness mandated by the Sarbanes-Oxley Act (SOX). They provide evidence that the mandate yield benefits for firms that translates into reduced cost of equity through mitigated information risk. They document that auditor confirmed changes in internal control effectiveness are accompanied with significant decreases in the cost of equity, and the range is from 0.5% to 1.5%.

Hermanson, 2005; Altuntas, Berry-Stölzle, and Hoyt, 2011). Kleffner, Lee, and McGannon's (2003) survey includes a question on the reasons to implement an ERM program; the top three reasons include the "influence of the risk managers," "encouragement from the board of directors," and "compliance with the Toronto Stock Exchange guidelines."

The second strand of literature examines the relationship between firm-specific characteristics and the firms' decision to adopt the ERM approach. Liebenberg and Hoyt (2003) find that firms with greater financial leverage are more likely to appoint a Chief Risk Officer (CRO); they interpret their result as evidence that firms start ERM programs to reduce information asymmetries regarding the firm's risk profile. Pagach and Warr (2011) document that a firm's likelihood to adopt ERM is determined by firm size, volatility, institutional ownership, and the CEO's risk taking incentives. For their subsample of banks, Pagach and Warr also document that banks with lower levels of Tier 1 capital are more likely to start an ERM program. Overall, Pagach and Warr's results support the notion that firms engage in ERM for direct economic benefit and not just to comply with regulation. In addition, Altuntas, Berry-Stölzle, and Hoyt (2012) point out that managerial career concerns provide incentives for managers to adopt ERM after periods of poor performance. Consistent with that view, their results document that negative changes in past firm performance increase a firm's probability to adopt ERM.

A third strand of literature investigates the value implications of ERM adoption. Grace et al. (2013) use the detailed Tillinghast Towers Perrin ERM survey of the insurance industry, and provide evidence that ERM improves firm operating performance. More precisely, they document that firms with ERM programs experience higher levels of cost efficiency and return on assets. The authors also find that life insurers benefit more from the development and use of economic capital models than property-casualty insurers. Hoyt and Liebenberg (2011) examine the value implications of ERM program adoption in a two-equation treatment effects model, in which the first stage equation describes firms' selection of the ERM approach. Using Tobin's Q as a proxy for firm value, they document a positive relationship between firm value and ERM adoption. Eckles, Hoyt, and Miller (2014) find that firms with ERM programs experience a reduction in stock return volatility, which becomes stronger over time. They also find that firms' operating profits per unit of risk increase after ERM adoption.

2.2 ERM and its Impact on the Cost of Capital

A firm's cost of capital is directly impacted by its risk profile. In essence, investors require a higher rate of return, equivalently a higher cost of equity capital, from a more risky company compared to a less risky one (Brealey, Myers, and Allen, 2011). ERM coordinates risk management activities across all business units of a firm and treats risks with a holistic approach. Hence, natural hedges across various types of risks enable firms to reduce expenditures related to different risk management activities, optimizing resource allocation and improving capital efficiency as well as return on equity. Furthermore, ERM can reduce a firm's overall risk by reducing the firm's earnings volatility (Hoyt and Liebenberg, 2011). Treating risks in "silos", traditional risk management decreases earnings volatility from a specific risk source (e.g., fire risk, operational risk, commodity price risk, etc.). However, potential interdependencies among risk classes might be overlooked. In contrast, ERM offers a framework that integrates all risk management activities into one unified structure that assists the identification of such interdependencies. Thus, an ERM engagement not only reduces earnings volatility arising from specific risk sources, but also prevents aggregation of risk across different sources.

ERM adoption improves the information available to the firm about its risk profile. This information can be shared with investors, leading to an increase in transparency about the firm's future earnings distribution. Improved disclosures of risk profiles are especially important for firms with complex operations because such firms are difficult to evaluate from the outside. Thus, improved disclosures and information sharing with investors can help to mitigate information asymmetries. Theory proposes that greater information decreases cost of equity capital through mitigated transaction costs and reduced estimation risk (see, e.g., Demsetz, 1968; Copeland and Galai, 1983; Amihud and Mendelson, 1986; Coles, Loewenstein, and Suay, 1995), and empirical studies (see, e.g., Verrecchia, 2001; Lambert, Leuz, and Verrecchia, 2007; Hail and Leuz, 2009) provide evidence supporting this argument. In addition, improved disclosures of risk profiles can serve as a signal of firms' commitment to risk management.

An additional benefit of an ERM program is simply a better risk identification process. ERM is a structured approach to look at all risks faced by the enterprise in a holistic way, which may screen for risks outside the standard risk silos and identify previously overlooked threats to the firm. Improved risk identification allows firms to choose the most effective tool to manage the identified risks instead of passively retaining them.

It is important for firms to have a strong financial strength rating. Standard & Poor's as well as other rating agencies explicitly evaluate companies' ERM program as part of the rating process. Following its announcement in October 2005 that ERM would "become a separate, major category" of its analysis for insurers, Standard & Poor's declared in May 2008 that it would add an additional dimension to its "ratings process for nonfinancial companies through an

ERM review."[2] In February 2006, A.M. Best, the major rating agency in insurance industry, released a special report describing its increased focus on ERM in the rating process. Therefore, having a well-functioning outstanding ERM program positively impacts firms' rating, which is monitored by the outside investors. The link between ERM programs and financial strength ratings creates an additional channel through which ERM adoption should lead to a lower cost of capital. In summary, I can state the following testable hypothesis for ERM adopting firms:

Hypothesis**:** *ERM adoption reduces the cost of equity capital for firms.*

3. Data and Methodology

3.1 Sample

The primary objective of my empirical analysis is to estimate the relation between ERM and firm's cost of equity capital. I focus in my analysis on the U.S. insurance industry for two reasons. First of all, covering multiple industries might result in the spurious correlations arisen from the unobservable regulatory and market differences across industries. The insurance industry has the advantage that a significant portion of firms has adopted the ERM approach, providing the necessary variation for an empirical analysis. The focus of the analysis on firms' cost of capital naturally restricts my sample to publicly traded companies because cost of capital calculations require stock prices. Thus, my initial sample is drawn from the universe of publicly traded insurers (Standard Industrial Classification (SIC) System codes between 6311 and 6399) in the merged CRSP/Compustat database for the period 1996–2012. This sample consists of 371 insurers that have operated in any year during the 17-year period.

[2] Standard & Poor's Rating Services published the criteria for evaluating ERM as part of insurance rating and corporate rating initially in 2005 and 2008, respectively. The most updated criteria for insurers and corporate entities were in May 2013 and November 2012, respectively.

I exclude firms with missing Compustat data on sales, assets, or equity, and American Depository Receipts. Then I identify the sales distribution of each firm across different industries in the Compustat Segment database. Following Zhang, Cox, and Van Ness (2009), I categorize firms with less than 50% sales generated from the insurance segment as non-insurers and eliminate these firms from the sample. Next, I remove firms with insufficient stock return data from the CRSP monthly stock database. I then match the sample firms to the I/B/E/S database and eliminate firms that do not have analyst earnings forecasts in I/B/E/S. This first set of screenings reduces my sample to 250 firms, or 1587 firm-year observations, and I are able to calculate a valid cost of equity capital measure for each observation.[3] For this sample, I classify all firms as ERM adopters or non-adopters as outlined in the next section. This is the sample I used for my event study because that analysis only requires a valid cost of equity capital measure and the year in which a firm adopts an ERM program.[4] I will refer to this sample as the event study sample throughout the paper. My regression analysis includes a number of additional insurance specific control variables. Thus, I merge the firms in the sample with statutory accounting data filed with the National Association of Insurance Commissioners (NAIC), and I drop firms for which neither a property and casualty, a life, nor a health statement is available. I also eliminate firms for which a statement is available, but reported net premiums written are zero or negative. Note that I aggregate statutory statements filed for individual subsidiaries of an insurance group to the group level, controlling for double counting of intragroup shareholdings. My final sample for the regression analysis consists of 132 firms, or 761 firm-year observations.[5]

[3] The details of the cost of equity capital calculation are discussed in the section "Measure of Implied Cost of Equity Capital."

[4] This study employs two methodologies to examine whether ERM reduces firms' cost of equity capital. The first is an "event study" and the second is a treatment effect model. They are discussed in sections "Changes in Firms' Cost of Capital around the Adoption of ERM" and "Regression Model," respectively.

[5] The samples for different specifications of the regression are shown in Table 5, 6, 7, and 8, ranging from 761 to 884.

3.2 Measure of ERM Adoption

I follow the previous ERM literature and use a four-step procedure to classify firms as ERM adopter or non-adopters (see, e.g., Hoyt and Liebenberg, 2011; Pagach and Warr, 2011; Eckles, Hoyt, and Miller, 2012). In the first step, I conduct a comprehensive search of newswires and other media for statements about an ERM program; the search includes Factiva, LexisNexis, Google search, and other search engines. In the second step, I identify the firm's ERM activity through a detailed search in their financial reports and in data libraries including Thomson One, Mergent Online, and the U.S. Securities and Exchange Commission (SEC) filings. I search ERM-related key phrases and their abbreviations, in conjunction with the individual firm names. Key phrases used in the search include "enterprise risk management," "chief risk officer," "risk committee," "strategic risk management," "consolidated risk management," "holistic risk management," and "integrated risk management" in different variations. In the third step, I then manually review each search result to determine whether it is a true hit and the firm actually adopts an ERM program, or whether the search hit just mentions ERM in a different context. Such out-of-context search hits, as for example ERM product sales to clients, are ignored. Finally, I identify the earliest evidence of ERM adoption for each insurer based on the previous three steps and construct an *ERM* indicator variable. To be consistent with my cost of capital measure described in the next section, I code the *ERM* indicator for the current year equal to one if a firm adopts ERM between July 1st of the previous year and June 30th of the current year. The *ERM* indicator is set to zero for years prior to ERM adoption, and set to one for all years after ERM adoption. My events study sample consists of 112 firms that have adopted ERM by the end of 2012, and 138 firms that have not. My regression sample includes 89 firms that have adopted ERM by 2012, and 43 firms that have not. Figure 1 shows the cumulative number of sample firms with an ERM program over time. The black bars represent the number of ERM adopters in the event study, and the grey bars show the number of adopters in the regression sample.

3.3 Measure of Implied Cost of Equity Capital

The cost of equity capital is the rate of return required by the shareholders of a company on their investment. To measure that required or expected rate of return, I use an implied cost of equity capital estimate because such measures better explain variation in expected stock returns than realized stock returns (see, e.g., Gebhardt, Lee and Swaminathan, 2001; Pástor, Sinha, and Swaminathan, 2008).[6] More precisely, I follow Pástor, Sinha, and Swaminathan (2008) and Campbell, Dhaliwal, and Schwartz (2012), and estimate the implied cost of capital by using the Gebhardt, Lee, and Swaminathan (2001) model. Their model is a derivative of the dividend discount model that expresses firm value in terms of accounting numbers. The main idea is to equate the firm's market value to the discounted expected future residual income of its shareholders. Solving for the discount rate that balances the equation gives the implied cost of

[6] Another relatively crude measure of *ex ante* expected returns used in the literature is the average of *ex post* realized returns (see, e.g., Cummins and Rubio-Misas, 2006). However, that approach has been widely criticized for producing very noisy estimates of expected returns (see, e.g., Blume and Friend, 1973; Sharpe, 1978; Froot and Frankel, 1989; Elton, 1999). Elton (1999) supports this argument by showing that average realized returns can diverge substantially from expected returns over lengthy periods of time. Alternatively, expected returns can be estimated using asset pricing models such as the CAPM and the Fama and French (1993) three-factor model (FF3). However, cost of capital estimates based on asset pricing models are still based on realized returns, and Fama and French (1997) show that such estimates are imprecise and have huge standard errors. In their study, Fama and French (1997) use the CPAM and the FF3 to estimate the cost of capital for 48 different industries, excluding the financial services sector. There are also two recent studies using an asset pricing model based approach to investigate the cost of capital specifically for the insurance industry. Cummins and Phillips (2005) estimate the cost of equity for property-liability insurance companies using the CAPM and FF3 models, and then further decompose companies' overall cost of capital by line of business using the full-information industry beta (FIB) method. Their results show that the cost of equity estimates based on the FF3 model are substantially higher than cost of capital estimates based on the CAPM, and that cost of capital estimates vary significantly across lines of business. Wen et al. (2008) compare the estimates of property-liability insurers' cost of capital based on the CAPM with estimates from the Rubinstein-Leland (RL) model. Their major finding is that the estimates based on the RL model are significantly higher than CAPM estimates for insurers with asymmetric return distributions and for small insurers. Thus, Wen et al. argue that insurers with asymmetric return distributions and small insurers should use the RL model to estimate their cost of capital

equity capital. The following paragraphs describe the model and the computation of the implied cost of capital measure; I refer to Gebhardt, Lee, and Swaminathan (2001) for further details.

The dividend discount model describes the price per share of common stock P_t at the end of year t as

$$P_t = \sum_{i=1}^{\infty} \frac{E_t(D_{t+i})}{(1+r_{icc})^i} \tag{1}$$

where

$E_t(D_{t+i})$ = expected future dividends per share for period $t+i$, conditional on the information available at time t, and

r_{icc} = cost of equity capital at time t.

Assuming "clean surplus" accounting that requires all gains and losses affecting firms' book value to be included in earnings, the book value B_t at the end of year t can be expressed as the book value at the end of the previous year plus earnings minus dividends, i.e. $B_t = B_{t-1} + NI_t - D_t$. Using that relationship, Equation (1) can be rewritten in a way such that the price per share of common stock is expressed in terms of standard accounting numbers:

$$P_t = B_t + \sum_{i=1}^{\infty} \frac{E_t[(ROE_{t+i} - r_{icc})B_{t+i-1}]}{(1+r_{icc})^i} \tag{2}$$

where

B_t = book value per share at the end of period t,

NI_{t+i} = net income per share for period $t+i$, and

ROE_{t+i} = after-tax return on book equity for period $t+i$.

Equation (2) is based on an infinite series. Gebhardt, Lee, and Swaminathan (2001) then slice that infinite series into three parts for practical purposes. For the first three years, explicit earnings forecasts of financial analysts from the I/B/E/S database are used. From year t+4 to year t+12, earnings are implicitly forecasted by mean reverting the third period ROE to the twelfth period ROE which is assumed to be the industry median ROE. Note that I treat the life insurance industry and the non-life insurance industry as separate industries in this context.[7, 8] The simple linear interpolation between the year t+3 ROE and the industry median ROE is used for the mean reversion process. For year t+12 and beyond, the value is estimated by calculating year 12's present value of the residual income as a perpetuity. Such a modeling approach assumes that firms cannot sustain earnings above the industry mean in a competitive market, and that abnormally high earnings will return to the industry median in the long run.[9] The exact specification of the model is as follows:

$$P_t = B_t + \frac{FROE_{t+1} - r_{icc}}{(1+r_{icc})} B_t + \frac{FROE_{t+2} - r_{icc}}{(1+r_{icc})^2} B_{t+1} + TV_t, \qquad (3)$$

where the terminal value TV is defined as

$$TV_t = \sum_{i=3}^{T-1} \frac{FROE_{t+i} - r_{icc}}{(1+r_{icc})^i} B_{t+i-1} + \frac{FROE_{t+T} - r_{icc}}{r_{icc}(1+r_{icc})^{T-1}} B_{t+T-1},$$

and $FEPS_{t+i}$ = forecasted earnings per share for year $t + i$. More precisely, $FEPS_1$ and $FEPS_2$ are equal to the one- and two-year-ahead consensus earnings per share (EPS) forecasts, $FEPS_3$ is equal to the three-year-ahead consensus EPS forecast when available, and $FEPS_2 \cdot (1 + LTG)$ when not available, and LTG is the long-term growth EPS forecast,

[7] Following Gebhardt, Lee, and Swaminathan (2001), loss firms are excluded when calculating the industry median ROE.

[8] The classification in life versus non-life insurers is based on NAICS codes. I classify insurers with NAICS code of 524113 as life insurers and all others as non-life insurers.

[9] The 12 year time period after which firms earnings return to the industry median is chosen arbitrarily according to Gebhardt, Lee, and Swaminathan (2001). However, they also present robustness checks and conclude that the "results are very similar" if a 6, 9, 15, 18, or 21 year time period is used.

$FROE_{t+i}$ = forecasted return on equity (ROE) for period $t + i$. For years one through three, this variable is equal to $FEPS_{t+i} / B_{t+i-1}$. Beyond year three, $FROE_{t+i}$ is the linear interpolation between $FROE_{t+3}$ and the industry median ROE for the prior 5 years (excluding loss firm-years) on a rolling window basis,

B_{t+i} = $B_{t+i-1} + FEPS_{t+i} \cdot (1 - k)$,

k = current dividend payout ratio, which is the ratio of the actual dividends from the most recent fiscal year divided by earnings over the same time period for firms with positive earnings, or divided by 0.06*total assets for firms with negative earnings, and

T = forecast horizon, T= 12.

Solving Equation (3) for r_{icc} gives the implied cost of equity capital (ICC) for a specific firm and year. Consistent with the previous literature, I collect analysts' forecasts from the I/B/E/S database as of June of the following year, and I calculate the ICC as of June of that year (see, e.g., Gebhardt, Lee, and Swaminathan, 2001; Dhaliwal, Heitzman, and Li, 2006; Pástor, Sinha, and Swaminathan, 2008). Following prior studies (see, e.g., Campbell, Dhaliwal, and Schwartz, 2012), I winsorize this *ICC* measure from above at 0.5. Figure 2 presents the annual median cost of equity capital over the 1996 through 2012 period for all insurance companies in my sample, as well as for the two subsamples of life and non-life insurers. The graph is based on ICC measures from 250 firms, or 1587 firm-year observations.

3.4 Changes in Firms' Cost of Capital around the Adoption of ERM

To test whether ERM adoption reduces firm's cost of capital, I first employ an event study methodology similar to the approach used by Lee, Mayers, and Smith (1997). I adjust for industry-wide trends in the cost of capital over time by subtracting the industry average from the ICC measure of each firm. I then test for significant changes of this industry-adjusted ICC measure in the (*t*-1) to (*t*+1) event window around the year of ERM adoption.

More precisely, I compute the industry-adjusted change in firm *i*'s implied cost of capital in the event window as

$$\Delta AdjICC_i = AdjICC_{i,t+1} - AdjICC_{i,t-1}, \tag{4}$$

where $AdjICC_{i,t} = ICC_{i,t} - IndustryAverage_{i,t}$ represents firm *i*'s industry-adjusted cost of capital, $ICC_{i,t}$ denotes firm *i*'s firm-specific cost of capital, and $IndustryAverage_{i,t}$ is the average cost of capital across all sample firms in the industry. Note that I use three alternative ways to calculate the $IndustryAverage_{i,t}$. First, I use the entire insurance industry to calculate the industry average cost of capital for each year. Second, I distinguish between life insurers and non-life insurers based on the North American Industry Classification System (NAICS) and calculate the industry average separately for life insurers (NAICS code of 524113) and non-life insurers.[10] Third, I distinguish between five sectors defined by NAICS codes and calculating separate industry average cost of capitals for them; I classify the NAICS code of 524113 as the life insurance sector, 524114 as the health insurance sector, 524126 and 524128 as the property-

[10] Following the standard in the literature (see, e.g., Fama and French, 1997; Wen, Martin, Lai, and O'Brien, 2008; Hoyt and Liebenberg, 2011), I use the SIC codes to define the insurance industry when pulling data from Compustat, CRSP, and I/B/E/S. However, the Compustat Segment database on corporate sales only provides complete information by NAICS codes. I use the data to screen for insurance firms and obtain the *OthIndus* variable as described in the section "Discussion of ERM Determinants." In order to be consistent, I use NAICS codes to define different sectors/segments/sub-industries *within* the insurance industry.

casualty sector, 524127 as the title insurance sector, and 524130 as the reinsurance sector. Finally, I use the *t*-test and the Wilcoxon signed-ranks test to analyze whether the industry-adjusted change in firms' cost of capital around the adoption of an ERM program as defined in Equation (4) differs significantly from zero.

3.5 Regression Model

3.5.1 Model Specification and Econometric Considerations

My second test of ERM's impact on firms' cost of equity capital is based on a regression model. I follow prior literature and model the cost of capital as a function of firm-specific characteristics (see, e.g., Botosan and Plumlee, 2005; Hail and Leuz, 2006; Dhaliwal, Heitzman, and Li, 2006; Pástor, Sinha, and Swaminathan, 2008; Campbell, Dhaliwal, and Schwartz, 2012; Hahn, Ogneva, and Ozbas, 2013). I then extend this baseline model to include the ERM adoption indicator. Since firms self-select to implement an ERM program and some of the factors affecting the selection decision may also impact the firms' cost of capital, I use a two-equation maximum-likelihood treatment effects model that jointly estimates firms' decision to adopt an ERM program and the effect of that decision (or treatment) on the firms' cost of capital. I adjust standard errors for clustering at the firm level. The specification of the model is as follows:

$$ICC_{i,t+1} = X_{it}\beta + \delta ERM_{it} + \varepsilon_{it}, \qquad (5)$$

where ICC_{it} is firm *i*'s implied cost of equity capital in year *t*, ERM_{it} is an indicator variable coded equal to 1 if firm *i* has adopted an ERM program in year *t*, 0 otherwise, X_{it} is a vector of control variables, and ε_{it} is the error term. A firm's choice to adopt an ERM program is then modeled as the outcome of an unobservable latent variable ERM^*_{it} which is a linear function of firm characteristics:

$$ERM_{it}^{*} = \omega_{it}\gamma + u_{it}, \tag{6}$$

where ω_{it} is a vector of firm characteristics, and u_{it} is the error term. Assuming that the observed decision is to adopt ERM if and only if the latent variable is positive, and assuming that the two error terms are bivariate normal with mean zero and a specific covariance matrix, the two equations can be estimated with the maximum-likelihood estimator. See Maddala (1983) for details. The following sections discuss the firm specific variables included as explanatory variables in Equations (5) and (6).

3.5.2 Variables Included in the Cost of Capital Equation

My selection of explanatory variables for the firms' cost of capital model (Equation (5)) is based on the previous literature (see, e.g., Gebhardt, Lee, and Swaminathan, 2001; Campbell, Dhaliwal, and Schwartz, 2012; Hahn, Ogneva, and Ozbas, 2013). As discussed in Campbell, Dhaliwal, and Schwartz (2012), the CAPM suggests a positive link between a stock's market beta and the corresponding firm's cost of equity capital, and hence I include beta as an explanatory variable in my model. I estimate each firm's beta based on the market model using the value-weighted CRSP (NYSE/AMEX) index and a minimum of twenty-four monthly returns over the prior sixty months.[11] I expect the coefficient on the *Beta* variable to be positive since the return demanded by shareholders should increase with market risk.

I expect firm size to be inversely related to the cost of capital because large firms are associated with lower default risk, resulting in lesser required yields by the equity holders (e.g., Botosan, 1997; Gode and Mohanram, 2003; Hou, van Dijk, and Zhang, 2012). I use the natural logarithm of the book value of assets to measure firm size.

[11] I follow Campbell, Dhaliwal, and Schwartz (2012) to use a minimum of twenty-four monthly returns.

Modigliani and Miller (1958) theorize that a firm's cost of equity, unlike its average cost of capital, is positively associated with the debt proportion in its capital structure, or in other words with the firm's leverage. Fama and French (1992) empirically demonstrate that the *ex post* mean stock returns are an increasing function of firms' leverage. Dhaliwal, Heitzman, and Li (2006) also document a positive relation between implied cost of equity capital and leverage. To capture differences in leverage across firms, I include a measure of leverage in my model. The *Leverage* variable is calculated as the ratio of the total book value of liabilities to the market value of equity.

I include the ratio of book to market value of equity in the model to controls for differences in growth opportunities across firms. Prior research (see, e.g., Fama and French, 1992, 1993; Berk, Green, and Naik, 1999; Petkova and Zhang, 2005) points out that stocks with a high book to market ratio, indicating relatively low growth opportunities, have relatively high systematic risk and time-varying risk, resulting in a high risk premium.[12] Consistent with that view, a number of empirical studies (see, e.g., Fama and French, 1992, 1993; Dhaliwal, Krull, Li, and Moser, 2005) provide evidence of a positive link between the book to market ratio and cost of capital. Thus, I expect a positive sign for the *BooktoMkt* variable. Following Campbell, Dhaliwal, and Schwartz (2012) I include firms' mean long-term growth forecasts from I/B/E/S as an additional control variable for growth opportunities in my model.

Forecasts from different analysts provide heterogeneous expectations and valuable information regarding a firm's earnings prospects. The dispersion of forecasts reflects analysts' uncertainty about a firm's expected earnings and, hence, can be interpreted as a measure of

[12] An alternative explanation for a positive link between the book to market ratio and cost of capital is based on overreaction-related mispricing (see, e.g., DeBondt and Thaler, 1987; Chopra, Lakonishok, and Ritter, 1992). The argument is that high book to market stocks earn an abnormally high implied risk premium because they are undervalued, and this high risk premium will continue until the mispricing is corrected.

information asymmetry between managers and outside investors or analysts (Madden, 1998; Botosan and Plumlee, 2005; Zhang, 2006). I include the standard measure of analysts' forecast dispersion in my model; *Foredispers* is calculated as the natural logarithm of the standard deviation of analyst earnings forecasts for the next year divided by the consensus earnings estimate for the same period.

Dividend payments change a firm's capital structure and may also signal the availability of growth opportunities in the firm of profitable business projects (see, e.g., Allayannis and Weston, 2001; Lang and Stulz, 1994). To control for any effect of dividend payments on firms' cost of capital, I include the *Dividend* indicator variable in my model. This indicator is coded equal to 1 if a firm pays a dividend in year *t*, 0 otherwise.

Prior studies find that a firm's cost of equity capital is significantly affected by the average cost of equity capital in its industry (see, e.g., Dhaliwal, Krull, and Li, 2007; Campbell, Dhaliwal, and Schwartz, 2012). Even though I only focus on the insurance industry, that industry has several sectors with diverse business models. To control for the effects across different sectors, I divide the insurance industry into three separate segments defined by the NAICS codes, and add the mean cost of equity capital for each sector as a control variable to my model. More specifically, I categorize the NAICS code of 524113 as the life sector, 524114 as the health sector, and 524126, 524127, 524128, and 524130 as the property-casualty sector.[13] In addition, I include year dummies in the *ICC* equation to control for variation in the cost of capital over time.

[13] I only define three insurance sectors in the treatment effects model sample, because the requirement of various control variables reduces the sample size. As a result, the observations in the title insurance sector and reinsurance sector become so few that they do not justify the separate categorizations. However, I define five sectors in the "event study," since the observations in these two sectors justify the separate categorizations.

3.5.3 Variables Included in the ERM Equation

My selection of explanatory variables for the ERM model (Equation (6)) is also based on the previous literature (see, e.g., Hoyt and Liebenberg, 2011; Pagach and Warr, 2011). A substantial number of studies find evidence that ERM adoption is more likely among larger firms (see, e.g., Colquitt, Hoyt, and Lee, 1999; Hoyt, Merkley, and Thiessen, 2001; Beasley, Clune, and Hermanson, 2005; Standard & Poor's, 2005). Explanations for the positive relationship between firm size and ERM adoption include the arguments that larger firms are more complex and face a wider spectrum of heterogeneous risks and may, hence, benefit more from a holistic approach towards risk identification, and that larger firms can spread the fixed costs of running an ERM program over multiple business units. To control for differences in size across firms, I include the natural logarithm of the firms' book value of assets in my model.

Liebenberg and Hoyt (2003) argue that firms with greater financial leverage should benefit more from reducing earnings volatility by managing their risks in an enterprise wide fashion, and their empirical results support that view. On the other hand, the implementation of an ERM program requires a substantial initial investment, and firms with higher levels of capital or lower levels of leverage may find it easier to start a new ERM program. Therefore, I do not have a clear expectation about the impact of leverage on firms' likelihood to adopt an ERM program. To capture any possible effect, my model includes the ratio of the total book value of liabilities to the market value of equity as a measure of firm leverage.

Firms with a high book-to-market ratio are usually large, established firms with substantial franchise value, whereas those with a low book-to-market ratio have most of their growth opportunities still ahead. Thus, I expect ERM implementation to be more valuable to firms with a high book-to-market ratio, since ERM adoption allows these firms to protect their franchise value. To control for differences in the book-to-market ratio across firms, I include the *BooktoMkt* variable in my model; this variable is calculated as the ratio of the book value of equity to the market value of equity.

Implementing an ERM program is a challenging task that requires substantial resources. If a company is involved in merger and acquisition (M&A) activities, it may not be able to devote additional resources to the implementation of an ERM program. Therefore, I expect a negative relationship between recent M&A activities and a firm's probability of starting an ERM program. To control for differences in M&A activities across firms, I add a *RecentM&A* measure to my model; it is calculated as the ratio of intangible assets to the book value of total assets. A merger or an acquisition usually results in a significant amount of goodwill and other intangible assets for companies (see, e.g., Caves, 1989; Dubin, 2007; Boone and Mulherin, 2008).[14] Hence, the fraction of intangible assets relative to the total assets can be interpreted as a measure of recent M&A activities.[15]

If an insurance company belongs to a conglomerate with firms from other industries, the board may include members without insurance specific expertise. For such a conglomerate, ERM

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[14] Boone and Mulherin (2008) study 308 U.S. corporate takeovers during an 11-year period, and find that the ratio of intangible assets to the total assets of the target firms averages 65% across the sample at the time of M&As.

[15] To examine whether my measure really captures M&A activities, I sort my sample firm-year observations into deciles with respect to the ratio of intangible assets to total assets. I then specifically examine the 10-K reports to the SEC from the companies in the largest decile. I find strong evidence linking firms' intangible assets fraction to their recent merger and acquisition activities. Three representative examples include Wellpoint, Inc., UnitedHealth Group, Inc., and Fidelity National Financial, Inc. Specifically, on page 32 in the 2008 10-K form of Wellpoint, Inc., it states that "Due largely to our past mergers and acquisitions, goodwill and other intangible assets represent a substantial portion of our assets. Goodwill and other intangible assets were approximately $22.3 billion as of December 31, 2008, representing approximately 46% of our total assets and 104% of our consolidated shareholders' equity at December 31, 2008. If we make additional acquisitions it is likely that we will record additional intangible assets on our consolidated balance sheets." On page 40 in the 2005 10-K form of UnitedHealth Group, Inc., it states that "Due largely to our recent acquisitions, goodwill and other intangible assets represent a substantial portion of our assets. Goodwill and other intangible assets were approximately $18.2 billion as of December 31, 2005, representing approximately 44% of our total assets. If we make additional acquisitions it is likely that we will record additional intangible assets on our books." On page 27 in the 2001 10-K form of Fidelity National Financial, Inc., it states that "We have made acquisitions in the past that resulted in recording a significant amount of goodwill. As of December 31, 2001, cost in excess of net assets acquired, net, was $808.6 million, of which $762.3 million relates to goodwill recorded in connection with the Chicago Title merger in 2000."

with its focus on identifying, measuring, aggregating, and communicating risk across the entire corporation may be especially helpful to ensure that all board members, regardless of insurance specific expertise, understand the firm's risk profile. Thus, I include the indicator variable *OthIndus* in my model; this variable is coded equal to one for firms with positive sales outside the insurance industry (NAICS codes less than 524100 or greater than 524199), and zero otherwise.

Insurers' lines of business diversification may also impact the ERM adoption decision. However, the direction of this effect is unclear. On the one hand, more diversified insurers are more complex and may, hence, benefit more from an ERM program than their more focused counterparts. On the other hand, more diversified insurers should already benefit from a substantial coinsurance effect and, hence, additional expected benefits from an ERM program may be marginal and hardly worth the investment, especially if implementation cost is increasing in the number of lines an insurer writes. To capture any effect of line of business diversification on ERM adoption, I include the *Divers* variable in my model. This variable is calculated as one minus the Herfindahl index of net premiums written across all 47 P/C, life and health insurance lines.[16]

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[16] The by line Herfindahl index is calculated across 47 business lines. For P/C insurance business, I collect the Net Premiums Written (NPW) by line from the Underwriting and Investment Exhibit (Part 1B – Premiums Written) in the NAIC annual statements. Based on their characteristics, I combine several lines together as follows. From the statutory data, Fire and Allied lines is defined as the sum of "Fire" and "Allied lines;" Accident and Health is defined as the sum of "Group Accident and Health," "Credit Accident and Health," and "Other Accident and Health;" Medical Malpractice is defined as the sum of "Medical Malpractice–Occurrence" and "Medical Malpractice–Claims Made;" Products Liability is defined as the sum of "Products Liability–Occurrence" and "Products Liability–Claims Made;" Auto is defined as the sum of "Private Passenger Auto Liability," "Commercial Auto Liability," and "Auto Physical Damage;" Reinsurance is defined as the sum of "Nonproportional Assumed Property," "Nonproportional Assumed Liability," and "Nonproportional Assumed Financial Lines." Therefore, I obtain 25 P/C lines, and they are Accident and Health, Aircraft, Auto, Boiler and Machinery, Burglary and Theft, Commercial Multi-Peril, Credit, Earthquake, Farmowners, Financial Guaranty, Fidelity, Fire and Allied lines, Homeowners, Inland Marine, International, Medical Malpractice, Mortgage Guaranty, Ocean Marine, Other, Other Liability, Products Liability, Reinsurance, Surety, Workers' Compensation, and Warranty. For life insurance business, I collect the NPW by line from the Exhibit -1 Part 1 – Premiums and Annuity Considerations for Life and Accident and Health Contracts in the NAIC annual statements. The 10 life insurance lines are Industrial Life,

I include three indicator variables to control for the potential heterogeneity in the likelihood of ERM adoption across the three insurance industry sectors. The three indicators *PCPrem, LifePrem,* and *HlthPrem* are coded equal to one if firms have positive net premiums written in the P/C, life, or health insurance segments respectively, and zero otherwise. I expect P/C insurers to be more likely to adopt ERM because the models used to aggregate risks within an ERM framework are closely related to those models employed in the actuarial pricing of P/C insurance contracts (Wang and Faber, 2006), reducing the cost of ERM adoption for P/C insurance companies.[17]

Given the common goal of reducing income volatility, reinsurance and ERM may act as substitutes (see, e.g., Cole and McCullough, 2006). If the volatility is effectively controlled by reinsurance use, the additional benefits from an ERM program may be minimal, resulting in a decreased likelihood of ERM adoption. To control for differences in reinsurance use across insurers, I include the *Reinsuse* variable in the model. This variable is calculated as the ratio of reinsurance ceded to direct premiums written plus reinsurance assumed (see, e.g., Cummins, Phillips, and Smith, 2001; Berry-Stölzle et al., 2012).[18]

Pagach and Warr (2010, 2011) argue that financial slack may be correlated with ERM adoption. If a firm's risk management program focuses on reducing the probability of bankruptcy

Ordinary Life Insurance, Ordinary Individual Annuities, Credit Life (Group and Individual), Group Life Insurance, Group Annuities, Group Accident and Health, Credit Accident and Health (Group and Individual), Other Accident and Health, and Aggregate of All Other Lines of Life Business. For health insurance business, I collect the NPW by line from the Underwriting and Investment Exhibit (Part 1 – Premiums) in the NAIC annual statements. The 12 health insurance lines are Comprehensive (Hospital and Medical), Dental Only, Disability & Long-Term Care & Stop Loss and Other, Disability Income, Federal Employee Health Benefits Plan, Long-Term Care, Medicare Supplement, Other Health, Stop Loss, Title XIX Medicaid, Title XVIII Medicare, and Vision Only.

[17] In addition, there is more guidance for P/C insurers how to implement an ERM program. In May 2013 Standard & Poor's published an ERM rating criteria guide for insurers. The ERM rating guidelines are very detailed for P/C insurers, less so for health insurers and life insurers.

[18] More precisely, given the inclusion of P/C, life, and health insurance sectors, the numerator of *Reinsuse* is calculated as the sum of reinsurance ceded by life subsidiaries, by health subsidiaries, and to non-affiliates by P/C subsidiaries; the denominator is computed as the sum of total direct premiums written by P/C, life, and health subsidiaries, and total reinsurance assumed by life subsidiaries, by health subsidiaries, and from non-affiliates by P/C subsidiaries.

the firm may hold additional funds *and* adopt an ERM program to achieve its goal. To capture the effect of slack on ERM adoption, I include the fraction of cash and marketable securities to total assets in my model.

ERM adoption should also be correlated with firms' earnings volatility (see, e.g., Liebenberg and Hoyt, 2003; Hoyt and Liebenberg, 2011; Pagach and Warr, 2010, 2011). One of the goals of an ERM program is to stabilize earnings. Therefore, firms with more volatile earnings can benefit more from adopting ERM and should be more likely to actually start an ERM program. To control for differences in earnings volatility across firms, I include the *CV(EBIT)* variable in my model. This variable is calculated as the coefficient of variation of the quarterly earnings before interest and taxes (EBIT) for the previous three years.

Altuntas, Berry-Stölzle, and Hoyt (2012) argue that managerial career concerns about keeping their job influences the decision to adopt ERM. An ERM program reduces the volatility of earnings and, hence, improves the informativeness of earnings as a signal of the CEO's ability. In a career concern model it is optimal for a CEO with high initial reputation to only adopt ERM after a period of poor performance. Consistent with that view, Altuntas, Berry-Stölzle, and Hoyt (2012) document a positive relation between firms' likelihood to adopt ERM and adverse changes in past performance for a sample of German insurance companies. I include firms' 1-year percentage change in market value in my model to capture any effect of changes in past performance on ERM adoption.[19]

Lastly, I include year dummies in the *ERM* equation to control for time variation in the probability of firms to implement ERM programs. Table 1 summarizes the definition of all the variables in the study.

[19] Firms' market value is calculated as the product of the year-end closing stock price and the number of shares outstanding.

4. Results

4.1 Changes in Firms' Cost of Capital around the Adoption of ERM

In order to investigate whether firms' implied cost of capital significantly decreases around the implementation of ERM programs, I conduct an event study in the broad sense by testing for the significance in the *ICC* changes centered by the event of ERM adoptions. With the aim of gauging the "abnormal" changes in *ICC*, the measure is adjusted for the average time trend in the industry to control for industry-wide *ICC* fluctuation. The adjustment is conducted in three different ways: treating the insurance industry as whole, separating it into life and non-life sectors, or dividing it further into five sub-industries. I obtain the adjusted measures by subtracting the industry or sector average *ICC* from the firm specific *ICC*. The null hypothesis of my t-test states that the mean of the industry-adjusted change in *ICC* specified in Equation (4) is not significantly different from zero. The Wilcoxon signed-ranks test examines a similar version for the median. I employ a two-year event window of (t - 1, t + 1), which compares the firms' cost of capital one year after ERM adoption with that one year before.

Table 2 presents the results of the "event study." The mean and median changes in the cost of capital are negative and significantly different from zero in the event window for all three approaches of segmenting the insurance industry. When the *ICC* adjustment is done at the whole industry level, both mean and median are significant at 1%. Overall these results demonstrate that ERM adoption is indeed accompanied by a significant drop in firms' cost of capital. On average, the reduction in firm's cost of capital one year after ERM adoption ranges from 1.054 to 1.272 percentage points.

4.2 Treatment Effects Model

4.2.1 Summary Statistics

The multivariate treatment effects model uses substantially more control variables than the “event study.” When I require non-missing values for all relevant variables in the treatment effects model, the sample decreases to 761 firm-year observations, or 132 firms. Among these firms are 89 ERM users, or 359 ERM firm-years, accounting for 47.175% of all observations. Table 3 shows the descriptive statistics for all variables used in the treatment effects regression. Many of the statistics are similar to those reported by Hoyt and Liebenberg (2011). Specifically, the mean and median implied cost of equity capital across my sample are 12.824% and 12.191%, respectively, with the standard deviation being 3.924%.

4.2.2 Univariate Analysis

Means and medians of all variables across ERM adoption status are reported in Table 4. ERM adopters are systematically different from non-adopters. Most notably, the average ERM adopter has a higher cost of capital than the average non-adopter. However, when interpreting this result, it is import to keep in mind that a univariate analysis does not control for other factors that also play essential roles in affecting firms’ cost of capital. On average, ERM adopters tend to have a larger market beta, higher leverage, higher book-to-market ratio, lower long-term growth rate forecasts, lower growth in market value, higher earnings volatility, and ERM adopters pay out more dividends than non-adopters. All these characteristics may also contribute to a higher cost of capital. The treatment effects model presented in the next section examines the effect of ERM on firms’ cost of capital while controlling for other firm characteristics.

4.2.3 Treatment Effects Model Results

Table 5 exhibits the results of the maximum-likelihood treatment effects model that consists of two simultaneously estimated equations. The estimation results for the *ICC* equation are reported in the first column. First of all, the coefficient of *ERM* is negative and significant at the 1% level, which supports my primary hypothesis that ERM adoption reduces the cost of equity capital for firms. The coefficient estimate shows that the difference in cost of capital between firms with ERM program and those without is highly significant. ERM adoption reduces firms' cost of capital by 1.834 percent points on average. The coefficient of the *Size* variable is negative and significant, indicating that larger firms have a lower cost of capital than smaller firms. The results also show that firms with larger beta, greater financial leverage, a higher book-to-market ratio, or greater dispersion in analyst forecasts tend to have significantly higher cost of capital. These findings are consistent with the theoretical predictions as well as with the results in Campbell, Dhaliwal, and Schwartz (2012).

The results for the *ERM* equation are reported in the second column of Table 5. In accordance with my univariate results, *Size* and *HlthPrem* are significantly associated with ERM adoption. In addition, I find that *Leverage*, *RecentM&A*, *OthIndust*, *Divers*, *PCPrem*, and *LifePrem* are also significant determinants. Specifically, consistent with prior literature, I provide evidence that larger firms are more likely to engage in the ERM program. I also find that financial leverage is inversely linked with ERM adoption. Moreover, as expected, firms recently going through mergers and acquisitions or those already well diversified are less likely to adopt ERM; firms involved in industries other than their core insurance business are more likely to become ERM users. Lastly, in line with my expectation, insurers with net premiums written in the P/C or health insurance sector are more likely to implement ERM, while those with life insurance subsidiaries are less likely to be ERM adopters. Through the Wald test I find that the residuals from Equations (5) and (6) are not independent, which justifies my usage of the simultaneous equation system.

4.2.4 Robustness: Survival Dataset

Pagach and Warr (2011) argue that a hazard model is superior to a logit model in studying the determinants of CRO hires. A logit model assumes that all the observations for a firm are independent, but this assumption does not hold in estimating the parameters of an "event history dataset." A hazard model, however, effectively overcomes this problem by focusing on a so-called survival dataset. Such a dataset includes all firm-year observations of firms that do not adopt ERM. It also includes the observations of ERM adopting firms in the year in which they adopt an ERM program. All firm-year observations of ERM adopters after ERM adoption are removed from the dataset. After ERM adoption, firms are considered censored and no longer observed.

Working with a survival dataset has two advantages. First, estimating a logit or probit model on the full sample, including firm-year observations after ERM adoption, assumes that all the observations for a firm are independent. In other words, it assumes that a firm makes a separate ERM adoption decision every year. Thus, the assumption is basically that a firm can switch back and forth between having and not having an ERM program every year. However, I am not aware of any firm that has shut down an existing ERM program. Therefore, it is simply just a decision to adopt ERM. By dropping observations after ERM adoptions, the model focuses only on the decision to adopt ERM and is, hence, closer to reality. Second, by removing from the sample observations of ERM adopters in years after ERM adoption, the analysis focuses on the effect of ERM *adoption*. It ensures that the results are not confounded by firm-specific changes in the business environment of ERM adopters over longer time period.

Since a treatment effects model specification basically uses a binary choice model for the first-stage ERM equation, it is subject to the same criticism as stand-alone models on ERM adoption decisions. To show the robustness of my results, I therefore create a survival dataset by dropping firm-year observations of ERM adopting firms in the years after the adoption from the sample. I then re-estimate the treatment effects model with this survival dataset. The downside of such an approach is a further reduction in sample size and, hence, statistical power. The survival dataset consists of 100 firms, or 449 firm-year observations.

Table 6 reports the results of the treatment effects model with the survival dataset. The coefficients and signs are very similar to those in the full sample. Most importantly, I still find the significantly negative relation between *ICC* and *ERM*. The difference in cost of capital between ERM users and non-users is 2.712 percent points and, hence, slightly larger than the estimate in the full sample (1.834 percent points). This result indicates that the effect of ERM programs on firms' cost of capital is more pronounced in the first year after ERM adoption.

4.2.5 Robustness: Alternative Specifications of the ERM Equation

Table 7 displays the results for ten specifications of the *ERM* equation, while holding the specification of the *ICC* equation constant as reported in Table 5. My first *ERM* equation specification only includes the identifying variables in the treatment effects model reported in Table 5, which are *RecentM&A*, *PCPrem*, *LifePrem*, and *HlthPrem*. The other specifications progressively add one additional *ERM* determinant at a time. Panel A of Table 7 reports the *ICC* equation results for each specification of the *ERM* equation. Panel B displays the ERM coefficient in the *ICC* equation, in addition to the *ERM* equation results. Note that due to the fact that less control variables are required in some specifications, the sample size enlarges in the particular specifications. Six specifications contain 145 firms, or 834 observations. For all of the ten alternative specifications of the *ERM* equation, the significantly inverse relation between firms' cost of capital and ERM adoption is robust. The effect of ERM on firms' cost of equity capital ranges from -1.369% to -1.879%.

4.2.6 Robustness: Alternative Specifications of the ICC Equation

In a similar vein, I conduct a robustness check with eight alternative specifications of the *ICC* equation, leaving the *ERM* equation unchanged. The first *ICC* equation specification only includes the *size* variable in addition to the ERM indicator. Then I add one additional control variable at a time to the ICC model. Table 8 reports the *ICC* equation results for this robustness check. The largest sample consists of 137 firms, or 884 observations. The *ERM* coefficient is negative and significant for all *ICC* equation specifications.

5. Conclusion

ERM is a process that manages all risks faced by the firm in an integrated, holistic fashion. It has been argued that the resulting synergies between the different risk management activities, the focus on maintaining the probability of large negative cash flows within acceptable limits, and the improved transparency about the firm's risk profile lead to a reduction in the firm's cost of external financing, which increases firm value. To provide the first empirical support for this argument, my research directly examines the relationship between ERM adoption and firms' cost of equity capital.

My analysis is based on the sample of publicly traded U.S. insurance companies; focusing on just one industry avoids possible spurious correlations caused by unobservable differences across industries. I calculate firm's cost of capital by equating the firm's market value of equity with its discounted future cash flow estimates and solving for the required internal rate of return. I then test for an abnormal reduction in the cost of capital around the year of ERM adoption, and estimate a two-equation treatment effects model to assess the effect of ERM on firms' cost of capital. In both tests, ERM adoption is significantly associated with a reduction in firms' cost of capital. Overall, my results indicate that cost of capital benefits are one answer to the question how ERM can create firm value.

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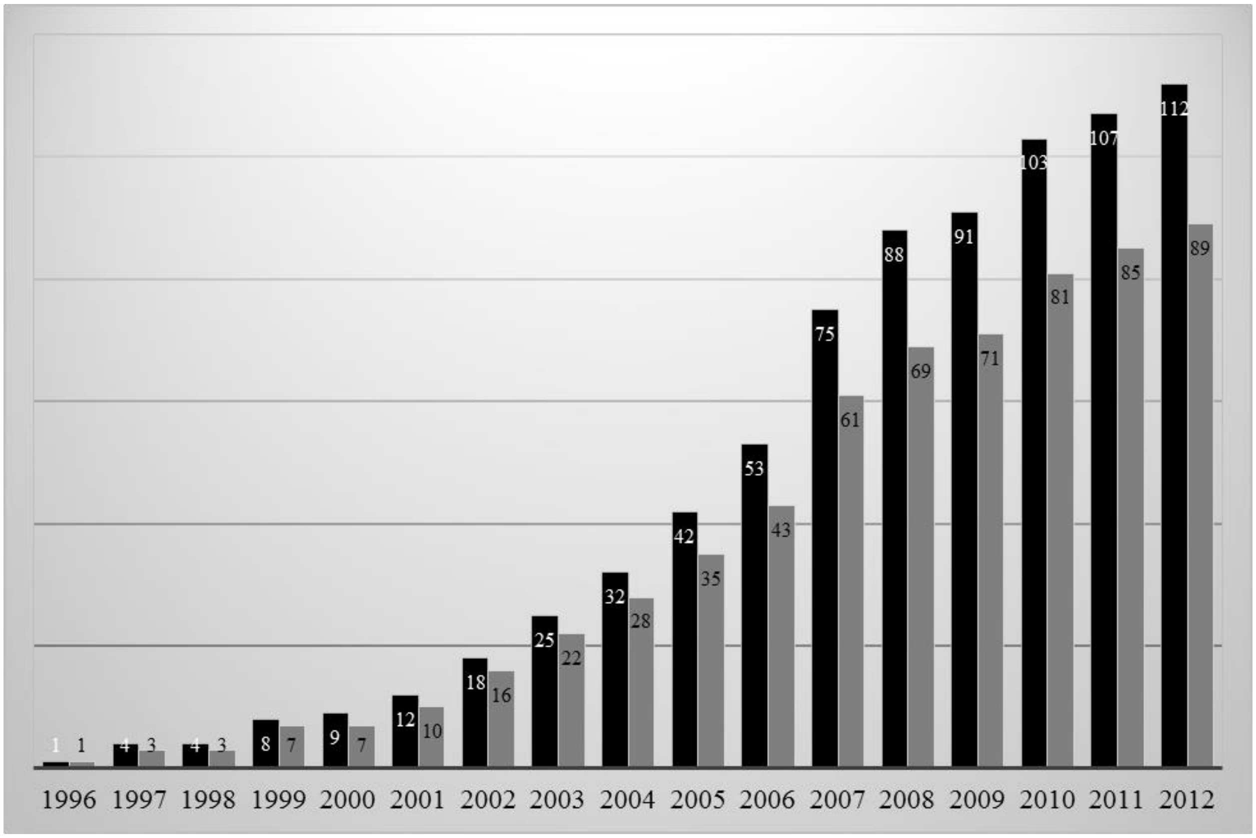
Figure 1
Cumulative Numbers of Sample Insurers Engaged in ERM by Year



Notes: Each black bar represents the number of ERM adopters in the sample based on the "event study" screenings, and each grey bar represents the number of adopters in the regression sample. I classify firms' ERM status through a comprehensive search of SEC filings, annual reports, newswires, and other media.

Figure 2
Insurers' Median Implied Cost of Equity Capital over Time

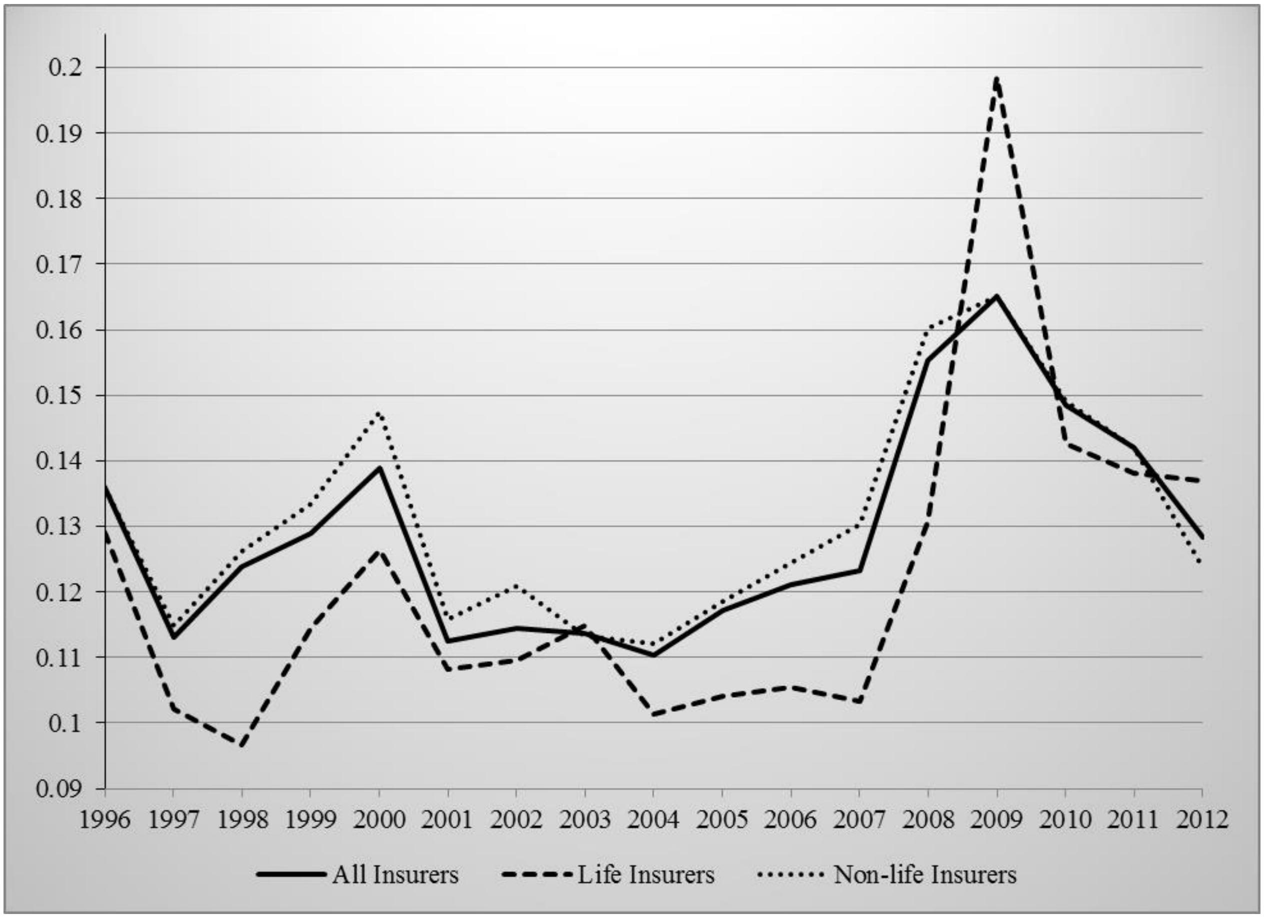


Table 1
Variable Definitions

Variable Name	Definition	Source
ICC	Firm's *ex ante* implied cost of equity capital calculated as in Gebhardt, Lee, and Swaminathan (2001) (see Equation (1)-(3) and the related discussion in the text)	I/B/E/S, Compustat, and CRSP
ERM	= 1 for firm-years > = year of first identifiable ERM activity, 0 otherwise	LexisNexis, Factiva, SEC filings, and other media
Beta	Beta estimated with the market model with a minimum of twenty-four monthly returns over the sixty prior months, using a value-weighted market index return	CRSP monthly stock files, Federal Reserve Board
Size	ln (Book value of assets)	Compustat (AT)
Leverage	Book value of liabilities / Market value of equity	Compustat ([AT − CEQ] / [PRCC × CSHO])
BooktoMkt	Book value of equity / Market value of equity	Compustat (CEQ / [PRCC × CSHO])
Foredispers	Ln (standard deviation of analyst estimates for next period's earnings / the consensus forecast for next period's earnings)	I/B/E/S
LongGrow	Firm's mean long-term growth forecast available in I/B/E/S	I/B/E/S
Dividend	= 1 if firm paid dividends in that year, 0 otherwise	Compustat (DVC > 0)
Sector_ICC	Average implied cost of equity capital in three different insurance sectors. I classify the NAICS code of 524113 as the life sector, 524114 as the health sector, and 524126, 524127, 524128, and 524130 as the property-casualty sector.	I/B/E/S, Compustat, and CRSP
RecentM&A	Intangible assets / Book value of assets	Compustat (INTAN / AT)
OthIndus	= 1 if positive sales in noninsurance industry NAICS code (<524100 or >524199), 0 otherwise	Compustat Segment database
Divers	1 – Herfindahl index of net premiums written across all lines of insurance	NAIC Statutory Statements for P/C, Life, and Health
PCPrem	= 1 if positve net premiums written in P/C insurance sector, 0 otherwise	NAIC Statutory Statements for P/C, Life, and Health
LifePrem	= 1 if positve net premiums written in life insurance sector, 0 otherwise	NAIC Statutory Statements for P/C, Life, and Health
HlthPrem	= 1 if positve net premiums written in health insurance sector, 0 otherwise	NAIC Statutory Statements for P/C, Life, and Health
Reinsuse	Reinsurance ceded/(direct premiums written + reinsurance assumed)	NAIC Statutory Statements for P/C, Life, and Health
Slack	Cash and short-term investments / Book value of assets	Compustat (CHE / AT)
CV(EBIT)	Coefficient of variation of quarterly earnings before interest and taxes in the past three years	Compustat (OIADPQ)
ValueChange	Firm value in year t – firm value in year $t-1$ / firm value in year $t-1$	Compustat ($PRCC_t \times CSHO_t - PRCC_{t-1} \times CSHO_{t-1}$)

Table 2
Changes in Firms' Cost of Capital around the Adoption of ERM

	Event Window	No. of Firms	Changes in *ICC*	
			Mean	*Median*
Industry Adjustment Based on Insurance Industry as a Whole	(t -1, t +1)	64	-0.01272***	-0.00692***
			(0.010)	(0.002)
Separate Industry Adjustments Based on Two Sectors Defined by Life vs. Non-life	(t -1, t +1)	64	-0.01221**	-0.00341***
			(0.017)	(0.009)
Separate Industry Adjustments Based on Five Sectors Defined by NAICS Codes	(t -1, t +1)	64	-0.01054**	-0.00516**
			(0.034)	(0.036)

Notes: The null hypotheses are that the mean and/or median of the changes in the industry-adjusted implied cost of equity capital as specified in Equation (4) are not different from zero. Firm i's industry-adjusted *ICC* is the difference between the firm's *ICC* in a particular year and the industry average *ICC* in that year. I use three ways to calculate insurance industry *ICC*. Firstly, I use insurance industry as a whole to calculate the industry average *ICC*. Secondly, I divide insurers into two sectors by life (NAICS code of 524113) vs. non-life insurers. Lastly, I separate them into five sectors defined by NAICS codes (NAICS code of 524113 as the life sector, 524114 as the health sector, 524126 and 524128 as the property-casualty sector, 524127 as the title insurance sector, and 524130 as the reinsurance sector). For the second and third approaches, after the classifications, I calculate each sector's average *ICC*, respectively, and use them as the minuend to compute the firm's industry-adjusted *ICC.* I use (t -1, t +1) event window, where t denotes the year when a firm adopts ERM. The t-test is used to examine the statistical significance of the means, and the Wilcoxon signed-ranks test is employed to examine the statistical significance of the medians; p-values appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3
Summary Statistics

	N	Mean	Std. Dev.	1st Quartile	Median	3rd Quartile
ICC	761	0.12824	0.03924	0.10526	0.12191	0.14390
ERM	761	0.47175	0.49953	0.00000	0.00000	1.00000
Beta	761	0.82310	0.58532	0.44587	0.70595	1.01302
Size	761	9.19088	1.79084	7.79654	9.04347	10.48114
Leverage	761	4.84371	7.07440	1.39090	2.61211	5.04246
BooktoMkt	761	0.80906	0.39535	0.54894	0.73445	0.98261
Foredispers	761	-3.87537	1.06388	-4.59006	-3.94481	-3.34739
LongGrow	761	11.57272	3.54004	10.00000	11.25000	13.28000
Dividend	761	0.76610	0.42359	1.00000	1.00000	1.00000
Sector_ICC	761	0.13945	0.00824	0.13294	0.14475	0.14475
RecentM&A	761	0.03438	0.07153	0.00073	0.00954	0.03073
OthIndus	761	0.00394	0.06270	0.00000	0.00000	0.00000
Divers	761	0.56476	0.28146	0.43451	0.67175	0.77588
PCPrem	761	0.78581	0.41053	1.00000	1.00000	1.00000
LifePrem	761	0.50197	0.50032	0.00000	1.00000	1.00000
HlthPrem	761	0.12221	0.32774	0.00000	0.00000	0.00000
Reinsuse	761	0.15103	0.16204	0.04797	0.10605	0.20473
Slack	761	0.10605	0.11810	0.04135	0.07267	0.11264
CV(EBIT)	761	0.21067	9.25970	0.22984	0.39504	0.75419
ValueChange	761	0.14932	0.44329	-0.09233	0.08809	0.31962

Notes: *ICC* is firm's *ex ante* implied cost of equity capital calculated as in Gebhardt, Lee, and Swaminathan (2001) (see Equation (1)-(3) and the related discussion in the text). *ERM* is an indicator variable that takes the value of 1 for firm-years starting from the first year of firms' ERM adoption, and 0 otherwise. ERM classification is based on a comprehensive search of SEC filings, annual reports, newswires, and other media. *Beta* is the capital market beta estimated based on the market model using a minimum of twenty-four monthly returns over the sixty prior months along with the value-weighted market index. *Size* is measured as the natural log of the book value of assets. *Leverage* is the fraction of the book value of liabilities to the market value of equity. *BooktoMkt* is defined as the ratio of the book value of equity to market value of equity. *Foredispers* is calculated as the natural logarithm of the standard deviation of analyst earnings forecasts for next year divided by the consensus earnings estimate for the same period. *LongGrow* is the firm's mean long-term growth rate by analysts' forecast from I/B/E/S. *Dividend* is an indicator that assigns the value of 1 if a firm paid dividends in a particular year, and 0 otherwise. *Sector_ICC* is the average implied cost of equity capital in three different insurance sectors. I classify the NAICS code of 524113 as the life sector, 524114 as the health sector, and 524126, 524127, 524128, and 524130 as the property-casualty sector. *RecentM&A* is equal to the ratio of intangible assets to the book value of assets. *OthIndus* is an indicator variable with value 1 for firm-years with positive sales outside the insurance industry (NAICS code <524100 or >524199), and 0 otherwise. *Divers* is equal to the complement of the Herfindahl index of net premiums written across all lines of insurance. *PCPrem*, *LifePrem*, and *HlthPrem* are indicators for firms that have positive net premiums written in P/C, life, and health insurance sector, respectively. *Reinsuse* is equal to the ratio of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Slack* is the fraction of cash and short-term investments in the book value of assets. *CV(EBIT)* is equal to the coefficient of variation of quarterly earnings before interest and taxes in the previous three years. *ValueChange* is defined as (firm value$_t$ − firm value$_{t-1}$) / firm value$_{t-1}$. Accounting and market data are collected from the Compustat Industrial and Compustat Segments databases. Firm and market returns are taken from the CRSP monthly stock database. Analysts' EPS forecasts are collected from I/B/E/S.

Table 4
Univariate Differences across ERM Status

Variable	(1) ERM = 1 Mean	(1) ERM = 1 Median	(2) ERM = 0 Mean	(2) ERM = 0 Median	Difference (1) - (2) Mean		Difference (1) - (2) Median	
ICC	0.13267	0.12809	0.12429	0.11628	0.00838	***	0.01181	***
Beta	0.99946	0.79669	0.66560	0.63897	0.33386	***	0.15772	***
Size	9.92030	9.75175	8.53949	8.26865	1.38081	***	1.48310	***
Leverage	5.90125	2.82631	3.89930	2.32549	2.00194	***	0.50082	***
BooktoMkt	0.91349	0.82789	0.71579	0.64767	0.19769	***	0.18022	***
Foredispers	-3.85042	-3.90399	-3.89764	-3.97029	0.04722		0.06630	
LongGrow	10.93942	10.50000	12.13828	12.00000	-1.19887	***	-1.50000	***
Dividend	0.83287	1.00000	0.70647	1.00000	0.12640	***	0.00000	
Sector_ICC	0.13948	0.14475	0.13943	0.14475	0.00005		0.00000	
RecentM&A	0.03469	0.00913	0.03410	0.01072	0.00059		-0.00159	
OthIndus	0.00557	0.00000	0.00249	0.00000	0.00308		0.00000	
Divers	0.57394	0.69443	0.55657	0.65921	0.01737		0.03522	*
PCPrem	0.80501	1.00000	0.76866	1.00000	0.03636		0.00000	
LifePrem	0.48468	0.00000	0.51741	1.00000	-0.03273		-1.00000	
HlthPrem	0.14763	0.00000	0.09950	0.00000	0.04813	**	0.00000	**
Reinsuse	0.14700	0.10563	0.15463	0.10702	-0.00763		-0.00139	
Slack	0.10518	0.08268	0.10683	0.06304	-0.00165		0.01964	***
CV(EBIT)	0.22917	0.45363	0.19415	0.34625	0.03501		0.10738	***
ValueChange	0.07051	0.04591	0.21970	0.16539	-0.14919	***	-0.11948	***
No. of firm-year obs.	359		402					

Notes: *ERM* is an indicator variable that takes the value of 1 for firm-years starting from the first year of firms' ERM adoption, and 0 otherwise. ERM classification is based on a comprehensive search of SEC filings, annual reports, newswires, and other media. *ICC* is firm's *ex ante* implied cost of equity capital calculated as in Gebhardt, Lee, and Swaminathan (2001) (see Equation (1)-(3) and the related discussion in the text). *Beta* is the capital market beta estimated based on the market model using a minimum of twenty-four monthly returns over the sixty prior months along with the value-weighted market index. *Size* is measured as the natural log of the book value of assets. *Leverage* is the fraction of the book value of liabilities to the market value of equity. *BooktoMkt* is defined as the ratio of the book value of equity to market value of equity. *Foredispers* is calculated as the natural logarithm of the standard deviation of analyst earnings forecasts for next year divided by the consensus earnings estimate for the same period. *LongGrow* is the firm's mean long-term growth rate by analysts' forecast from I/B/E/S. *Dividend* is an indicator that assigns the value of 1 if a firm paid dividends in a particular year, and 0 otherwise. *Sector_ICC* is the average implied cost of equity capital in three different insurance sectors. I classify the NAICS code of 524113 as the life sector, 524114 as the health sector, and 524126, 524127, 524128, and 524130 as the property-casualty sector. *RecentM&A* is equal to the ratio of intangible assets to the book value of assets. *OthIndus* is an indicator variable with value 1 for firm-years with positive sales outside the insurance industry (NAICS code <524100 or >524199), and 0 otherwise. *Divers* is equal to the complement of the Herfindahl index of net premiums written across all lines of insurance. *PCPrem*, *LifePrem*, and *HlthPrem* are indicators for firms that have positive net premiums written in P/C, life, and health insurance sector, respectively. *Reinsuse* is equal to the ratio of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Slack* is the fraction of cash and short-term investments in the book value of assets. *CV(EBIT)* is equal to the coefficient of variation of quarterly earnings before interest and taxes in the previous three years. *ValueChange* is defined as (firm value$_t$ − firm value$_{t-1}$) / firm value$_{t-1}$. Accounting and market data are collected from the Compustat Industrial and Compustat Segments databases. Firm and market returns are taken from the CRSP monthly stock database. Analysts' EPS forecasts are collected from I/B/E/S. The *t*-test is used to examine the statistical significance of difference in means. The nonparametric Wilcoxon rank sum test is used to examine the statistical significance of difference in medians. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5
Full Maximum-Likelihood Treatment Effects Estimates

	ICC (Equation 1)		*ERM* (Equation 2)	
ERM	-0.01834	(0.00454)***		
Beta	0.00514	(0.00293)*		
Size	-0.00572	(0.00149)***	0.67800	(0.08328)***
Leverage	0.00070	(0.00033)**	-0.03339	(0.01375)**
BooktoMkt	0.03425	(0.00609)***	0.10892	(0.35602)
Foredispers	0.00452	(0.00194)**		
LongGrow	-0.00038	(0.00040)		
Dividend	0.00852	(0.00530)		
Sector_ICC	0.34237	(0.21741)		
RecentM&A			-4.52230	(1.60875)***
OthIndust			1.95296	(0.39776)***
Divers			-0.99107	(0.45803)**
PCPrem			1.16379	(0.32318)***
LifePrem			-0.80652	(0.28973)***
HlthPrem			1.53842	(0.50661)***
Reinsuse			0.44138	(0.67036)
Slack			-1.41203	(1.10130)
CV(EBIT)			-0.00331	(0.00892)
ValueChange			-0.21058	(0.15592)
Constant	0.11597	(0.03721)***	-4.23503	(0.96896)***
No. of observations	761			
No. of clusters	132			
Log pseudolikelihood	1383.80			
Wald test of independent equations	6.95***			

Notes: *ICC* is firm's *ex ante* implied cost of equity capital calculated as in Gebhardt, Lee, and Swaminathan (2001) (see Equation (1)-(3) and the related discussion in the text). *ERM* is an indicator variable that takes the value of 1 for firm-years of ERM users starting from the first year of the ERM adoption, and 0 otherwise. ERM classification is based on a comprehensive search of SEC filings, annual reports, newswires, and other media. *Beta* is the capital market beta estimated based on the market model using a minimum of twenty-four monthly returns over the sixty prior months along with the value-weighted market index. *Size* is measured as the natural log of the book value of assets. *Leverage* is the fraction of the book value of liabilities to the market value of equity. *BooktoMkt* is defined as the ratio of the book value of equity to market value of equity. *Foredispers* is calculated as the natural logarithm of the standard deviation of analyst earnings forecasts for next year divided by the consensus earnings estimate for the same period. *LongGrow* is the firm's mean long-term growth rate by analysts' forecast from I/B/E/S. *Dividend* is an indicator that assigns the value of 1 if a firm paid dividends in a particular year, and 0 otherwise. *Sector_ICC* is the average implied cost of equity capital in three different insurance sectors. I classify the NAICS code of 524113 as the life sector, 524114 as the health sector, and 524126, 524127, 524128, and 524130 as the property-casualty sector. *RecentM&A* is equal to the ratio of intangible assets to the book value of assets. *OthIndus* is an indicator variable with value 1 for firm-years with positive sales outside the insurance industry (NAICS code <524100 or >524199), and 0 otherwise. *Divers* is equal to the complement of the Herfindahl index of net premiums written across all lines of insurance. *PCPrem*, *LifePrem*, and *HlthPrem* are indicators for firms that have positive net premiums written in P/C, life, and health insurance sector, respectively. *Reinsuse* is equal to the ratio of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Slack* is the fraction of cash and short-term investments in the book value of assets. *CV(EBIT)* is equal to the coefficient of variation of quarterly earnings before interest and taxes in the previous three years. *ValueChange* is defined as (firm value$_t$ − firm value$_{t-1}$) / firm value$_{t-1}$. Accounting and market data are collected from the Compustat Industrial and Compustat Segments databases. Firm and market returns are taken from the CRSP monthly stock database. Analysts' EPS forecasts are collected from I/B/E/S. I include the year dummies for 1997–2012 in both equations, but do not report them. Standard errors are adjusted for firm-level clustering, and are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 6
Full Maximum-Likelihood Treatment Effects Estimates (Survival Dataset)

	ICC (Equation 1)		*ERM* (Equation 2)	
ERM	-0.02712	(0.01270)**		
Beta	0.00055	(0.00528)		
Size	-0.00852	(0.00179)***	0.45508	(0.07958)***
Leverage	0.00133	(0.00059)**	-0.03187	(0.01597)**
BooktoMkt	0.04713	(0.00974)***	0.64680	(0.40110)
Foredispers	0.00216	(0.00208)		
LongGrow	0.00048	(0.00069)		
Dividend	0.00703	(0.00657)		
Sector_ICC	0.20011	(0.32498)		
RecentM&A			-2.84968	(1.41318)**
OthIndust			-2.86315	(0.00000)
Divers			-0.81611	(0.35789)**
PCPrem			0.44205	(0.32530)
LifePrem			-0.42883	(0.28029)
HlthPrem			0.61007	(0.42330)
Reinsuse			0.39629	(0.51669)
Slack			-0.97929	(1.05913)
CV(EBIT)			0.01080	(0.00861)
ValueChange			0.15568	(0.20525)
Constant	0.12245	(0.05536)**	-3.72671	(1.07359)***
No. of observations		449		
No. of clusters		100		
Log pseudolikelihood		827.76		
Wald test of independent equations		2.84*		

Notes: In the survival sample, I remove from the full sample the observations of ERM users following the year they adopted ERM. *ICC* is firm's *ex ante* implied cost of equity capital calculated as in Gebhardt, Lee, and Swaminathan (2001) (see Equation (1)-(3) and the related discussion in the text). *ERM* is an indicator variable that takes the value of 1 for ERM users in the year they adopted ERM, and 0 for ERM users in the years before ERM adoption as well as for all firm-years of ERM non-adopters. *Beta* is the capital market beta estimated based on the market model using a minimum of twenty-four monthly returns over the sixty prior months along with the value-weighted market index. *Size* is measured as the natural log of the book value of assets. *Leverage* is the fraction of the book value of liabilities to the market value of equity. *BooktoMkt* is defined as the ratio of the book value of equity to market value of equity. *Foredispers* is calculated as the natural logarithm of the standard deviation of analyst earnings forecasts for next year divided by the consensus earnings estimate for the same period. *LongGrow* is the firm's mean long-term growth rate by analysts' forecast from I/B/E/S. *Dividend* is an indicator that assigns the value of 1 if a firm paid dividends in a particular year, and 0 otherwise. *Sector_ICC* is the average implied cost of equity capital in three different insurance sectors. I classify the NAICS code of 524113 as the life sector, 524114 as the health sector, and 524126, 524127, 524128, and 524130 as the property-casualty sector. *RecentM&A* is equal to the ratio of intangible assets to the book value of assets. *OthIndus* is an indicator variable with value 1 for firm-years with positive sales outside the insurance industry (NAICS code <524100 or >524199), and 0 otherwise. *Divers* is equal to the complement of the Herfindahl index of net premiums written across all lines of insurance. *PCPrem*, *LifePrem*, and *HlthPrem* are indicators for firms that have positive net premiums written in P/C, life, and health insurance sector, respectively. *Reinsuse* is equal to the ratio of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Slack* is the fraction of cash and short-term investments in the book value of assets. *CV(EBIT)* is equal to the coefficient of variation of quarterly earnings before interest and taxes in the previous three years. *ValueChange* is defined as (firm value$_t$ − firm value$_{t-1}$) / firm value$_{t-1}$. Accounting and market data are collected from the Compustat Industrial and Compustat Segments databases. Firm and market returns are taken from the CRSP monthly stock database. Analysts' EPS forecasts are collected from I/B/E/S. I include the year dummies for 1997–2012 in both equations, but do not report them. Standard errors are adjusted for firm-level clustering, and are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 7
Sensitivity of the Cost of Capital Difference between ERM Adopters and Non-Adopters to Alternative Specifications of the *ERM* Equation

Panel A
ICC Equation Results

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ERM	-0.01369**	-0.01581***	-0.01586***	-0.01588***	-0.01577***	-0.01816***	-0.01827***	-0.01794***	-0.01879***	-0.01834***
	(0.00660)	(0.00533)	(0.00553)	(0.00558)	(0.00557)	(0.00584)	(0.00601)	(0.00604)	(0.00450)	(0.00454)
Beta	0.00499	0.00478	0.00495	0.00495	0.00497	0.00536	0.00539	0.00529	0.00521*	0.00514*
	(0.00346)	(0.00341)	(0.00342)	(0.00342)	(0.00342)	(0.00346)	(0.00347)	(0.00349)	(0.00291)	(0.00293)
Size	-0.00818***	-0.00686***	-0.00668***	-0.00669***	-0.00670***	-0.00649***	-0.00651***	-0.00655***	-0.00568***	-0.00572***
	(0.00192)	(0.00172)	(0.00169)	(0.00169)	(0.00169)	(0.00161)	(0.00162)	(0.00163)	(0.00149)	(0.00149)
Leverage	0.00108***	0.00107***	0.00096***	0.00096***	0.00096***	0.00094***	0.00093**	0.00094***	0.00070**	0.00070**
	(0.00037)	(0.00036)	(0.00036)	(0.00036)	(0.00036)	(0.00036)	(0.00036)	(0.00036)	(0.00033)	(0.00033)
BooktoMkt	0.03181***	0.03109***	0.03131***	0.03115***	0.03115***	0.03119***	0.03131***	0.03133***	0.03422***	0.03425***
	(0.00610)	(0.00599)	(0.00602)	(0.00629)	(0.00628)	(0.00633)	(0.00636)	(0.00635)	(0.00609)	(0.00609)
Foredispers	0.00617***	0.00642***	0.00645***	0.00645***	0.00645***	0.00631***	0.00627***	0.00623***	0.00455**	0.00452**
	(0.00222)	(0.00223)	(0.00223)	(0.00224)	(0.00224)	(0.00221)	(0.00222)	(0.00222)	(0.00194)	(0.00194)
LongGrow	-0.00010	-0.00008	-0.00008	-0.00008	-0.00008	-0.00010	-0.00011	-0.00011	-0.00038	-0.00038
	(0.00041)	(0.00041)	(0.00041)	(0.00041)	(0.00041)	(0.00041)	(0.00041)	(0.00041)	(0.00040)	(0.00040)
Dividend	0.00928	0.00882	0.00893	0.00895	0.00893	0.00904	0.00909	0.00925	0.00847	0.00852
	(0.00619)	(0.00605)	(0.00606)	(0.00604)	(0.00604)	(0.00604)	(0.00608)	(0.00610)	(0.00530)	(0.00530)
Sector_ICC	0.25036	0.31472	0.30905	0.30954	0.30848	0.32710	0.32841	0.32989	0.34492	0.34237
	(0.22333)	(0.21869)	(0.21784)	(0.21819)	(0.21829)	(0.21979)	(0.21991)	(0.22012)	(0.21798)	(0.21741)
Constant	0.15080***	0.13306***	0.13251***	0.13269***	0.13285***	0.12981***	0.12960***	0.12931***	0.11569***	0.11597***
	(0.04195)	(0.03906)	(0.03880)	(0.03872)	(0.03874)	(0.03865)	(0.03867)	(0.03877)	(0.03727)	(0.03721)
No. of obs.	834	834	834	834	834	834	832	832	761	761
No. of clusters	145	145	145	145	145	145	144	144	132	132
Log pseudolikelihood	1275.93	1356.14	1359.69	1359.72	1359.99	1367.07	1362.52	1363.85	1383.25	1383.80
Wald test	4.81**	12.26***	11.45***	11.13***	11.17***	11.71***	11.60***	11.68***	7.38***	6.95***

(*Continued*)

Panel B

ERM Equation Results

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ERM coefficient in *ICC* equation	-0.01369**	-0.01581***	-0.01586***	-0.01588***	-0.01577***	-0.01816***	-0.01827***	-0.01794***	-0.01879***	-0.01834***
Size		0.57874***	0.61537***	0.61313***	0.61296***	0.66728***	0.66588***	0.65124***	0.68227***	0.67800***
		(0.07723)	(0.07869)	(0.08047)	(0.08032)	(0.07617)	(0.07606)	(0.07753)	(0.08396)	(0.08328)
Leverage			-0.02640**	-0.02490*	-0.02523*	-0.03291**	-0.03302**	-0.03290**	-0.03367**	-0.03339**
			(0.01060)	(0.01353)	(0.01363)	(0.01442)	(0.01434)	(0.01452)	(0.01407)	(0.01375)
BooktoMkt				-0.05849	-0.04841	0.13644	0.14061	0.14891	0.15170	0.10892
				(0.35416)	(0.35719)	(0.33890)	(0.33586)	(0.33473)	(0.35604)	(0.35602)
OthIndust					1.87965***	1.88382***	1.88271***	1.84286***	1.98574***	1.95296***
					(0.33966)	(0.34542)	(0.35651)	(0.37137)	(0.40666)	(0.39776)
Divers						-0.90522**	-0.91687**	-0.89533**	-1.00252**	-0.99107**
						(0.46089)	(0.45745)	(0.44868)	(0.45645)	(0.45803)
Reinsuse							0.02846	0.05639	0.39633	0.44138
							(0.66386)	(0.64357)	(0.67177)	(0.67036)
Slack								-1.24869	-1.51554	-1.41203
								(1.18106)	(1.11260)	(1.10130)
CV(EBIT)									-0.00051	-0.00331
									(0.00896)	(0.00892)
ValueChange										-0.21058
										(0.15592)
Identifying Variables										
RecentM&A	-3.30086*	-3.88851**	-4.33419**	-4.30370**	-4.33714**	-4.71276***	-4.66337***	-4.78828***	-4.46336***	-4.52230***
	(1.74649)	(1.74109)	(1.78376)	(1.77825)	(1.78330)	(1.76506)	(1.74998)	(1.75155)	(1.58423)	(1.60875)
PCPrem	0.50549*	0.79781***	0.71756***	0.72834**	0.72302**	0.92277***	0.92239***	0.91848***	1.15737***	1.16379***
	(0.28139)	(0.28371)	(0.27694)	(0.28344)	(0.28417)	(0.31301)	(0.31030)	(0.31355)	(0.32301)	(0.32318)
LifePrem	0.28164	-0.94563***	-0.86797***	-0.86557***	-0.86845***	-0.70899**	-0.70716**	-0.74835***	-0.80457***	-0.80652***
	(0.24770)	(0.30205)	(0.30228)	(0.30028)	(0.30032)	(0.29278)	(0.29195)	(0.28670)	(0.29065)	(0.28973)
HlthPrem	0.32700	1.01978**	0.92928**	0.91842*	0.91873*	1.09744**	1.08992**	1.45365***	1.54112***	1.53842***
	(0.42673)	(0.45839)	(0.46695)	(0.47279)	(0.47304)	(0.45855)	(0.45631)	(0.52641)	(0.49887)	(0.50661)
Constant	1.23432***	-3.79961***	-3.88687***	-3.82083***	-3.84426***	-4.23746***	-4.22831***	-3.96170***	-4.31632***	-4.23503***
	(0.43477)	(0.78015)	(0.76164)	(0.91712)	(0.91538)	(0.84149)	(0.84228)	(0.85897)	(0.97600)	(0.96896)
No. of obs.	834	834	834	834	834	834	832	832	761	761
No. of clusters	145	145	145	145	145	145	144	144	132	132
Log pseudolikelihood	1275.93	1356.14	1359.69	1359.72	1359.99	1367.07	1362.52	1363.85	1383.25	1383.80
Wald test	4.81**	12.26***	11.45***	11.13***	11.17***	11.71***	11.60***	11.68***	7.38***	6.95***

Notes: In Panel A, the dependent variable is *ICC*. In Panel B, the dependent variable is *ERM*. All variables are defined in Table 1. Year dummies are included in each regression. Standard errors are adjusted for firm-level clustering, and are reported in parentheses below each coefficient estimate. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 8
Sensitivity of the Cost of Capital Difference between ERM Adopters and Non-Adopters to Alternative Specifications of the *ICC* Equation

ICC Equation Results

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ERM	-0.03565***	-0.01851**	-0.01705**	-0.01679***	-0.01333**	-0.01368**	-0.01627***	-0.01834***
	(0.00813)	(0.00754)	(0.00861)	(0.00468)	(0.00558)	(0.00553)	(0.00538)	(0.00454)
Size	-0.00118	-0.00298**	-0.00416***	-0.00431***	-0.00547***	-0.00572***	-0.00628***	-0.00572***
	(0.00153)	(0.00126)	(0.00130)	(0.00114)	(0.00129)	(0.00134)	(0.00144)	(0.00149)
BooktoMkt		0.04707***	0.04371***	0.04087***	0.03557***	0.03575***	0.03627***	0.03425***
		(0.00419)	(0.00416)	(0.00517)	(0.00550)	(0.00545)	(0.00543)	(0.00609)
Beta			0.00844**	0.00613**	0.00396	0.00411	0.00466	0.00514*
			(0.00342)	(0.00293)	(0.00287)	(0.00287)	(0.00294)	(0.00293)
Foredispers				0.00489**	0.00500**	0.00481**	0.00508***	0.00452**
				(0.00199)	(0.00201)	(0.00200)	(0.00192)	(0.00194)
Leverage					0.00064**	0.00057**	0.00053*	0.00070**
					(0.00027)	(0.00027)	(0.00027)	(0.00033)
LongGrow						-0.00062	-0.00038	-0.00038
						(0.00043)	(0.00040)	(0.00040)
Dividend							0.00945*	0.00852
							(0.00509)	(0.00530)
Sector_ICC								0.34237
								(0.21741)
Constant	0.17781***	0.12043***	0.12512***	0.14739***	0.16024***	0.16955***	0.16781***	0.11597***
	(0.01577)	(0.01316)	(0.01267)	(0.01585)	(0.01673)	(0.01860)	(0.01816)	(0.03721)
No. of obs.	884	884	883	776	776	761	761	761
No. of clusters	137	137	137	132	132	132	132	132
Log pseudolikelihood	1341.76	1449.53	1453.51	1391.20	1394.89	1376.17	1381.77	1383.80
Wald test	12.54***	4.77**	3.29*	6.64***	3.74*	4.06**	4.77**	6.95***

Notes: The dependent variable is *ICC*. The ERM determinants equation is held constant at the most comprehensive specification (Specification 10 in Table 7). All variables are defined in Table 1. Year dummies are included in each regression. Standard errors are adjusted for firm-level clustering, and are reported in parentheses below each coefficient estimate. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

ESSAY TWO:

LOCAL RELIGIOUS BELIEFS AND INSURANCE COMPANIES' RISK-TAKING BEHAVIORS

1. Introduction

In the aftermaths of the recent financial crisis, risk-taking in the financial services sector has received increased attention from policymakers, regulators as well as from researchers, resulting in a growing body of literature on systemic risk and risk-taking in general (see, e.g., John, Litov, Yeung, 2008; Fields, Gupta, Prakash, 2012; Ho, Lai, and Lee, 2013). Another growing body of literature focuses on behavioral or cultural aspects of business decisions. While most behavioral biases and local cultures are hard to observe and measure, religious beliefs can be captured with a relatively simple measure: affiliation with a church. A number of studies, hence, empirically examine the effects of local religious beliefs on business decisions of firms headquartered in that region. There is evidence that local religious beliefs indeed impact corporate investments (Hilary and Hui, 2009; Kumar, Page, and Spalt, 2011), earnings management (Grullon, Kanatas, and Weston, 2010; Dyreng, Mayew, and Williams, 2012), tax avoidance (McGuire, Omer, and Sharp, 2012), and manager option grants and compensation packages (Grullon, Kanatas, and Weston, 2010), as well as investment decisions of mutual funds (Shu, Sulaeman, and Yeung, 2012). However, little evidence exists regarding behavioral or cultural aspects of risk-taking decisions in financial institutions. Given that the recent financial crisis originated from the financial services sector and that 7 out of the 10 largest bankruptcies in U.S. history occurred during the financial crisis (New Generation Research, 2013), I find it particularly important to study risk-taking behaviors in financial services firms.

The goal of my research is to empirically examine the effects of local religious beliefs on risk-taking of financial institutions. I focus on a particular type of financial institutions, insurance companies, because they take risks as a result of their unique business model. In other words, the insurance industry is in the business of risk, which provides an ideal environment for studying risk-taking behaviors. Within the industry, there are heterogeneities in risk-taking among different major segments. Therefore, exploring sub-groups of insurers is necessary. I focus on life insurance companies in particular for the following reasons. First, in the recent financial crisis the U.S. Treasury initiated the Troubled Asset Relief Program (TARP), and the fund takers in the insurance industry were two life insurance companies.[1] This motivates the special interest in studying life insurers' risk-taking. Second, life insurance companies are major investors in the financial services sector. They have significant portion of investment in capital markets to meet long-term obligations to policyholders. Given prior evidence that religion impacts corporate investments, I expect local religious beliefs to have noticeable effects on life insurers. Local religious beliefs are one important component of local culture. Thus, my research provides evidence to what degree local culture and its norms influence decisions of insurance companies.

There are two theoretical arguments why insurers' risk-taking behaviors may be impacted by the local culture. Social identity theories (see, e.g., Tajfel, 1978; Turner and Reynolds, 2010) suggest that people identify themselves with relevant social groups and derive utility from conforming to group norms. Therefore, individuals might adjust their behavior to fit to their social environment. In addition, managers and employees in the labor market might choose to join a firm headquartered in a region with a culture they feel comfortable with (see, e.g., Schneider, 1987; Hilary and Hui, 2009).

Prior literature documents a strong and robust relationship between religious beliefs and risk attitudes of both individuals and corporations. Individual Protestants tend to exhibit more risk-aversion than individual Catholics (see, e.g., Barsky et al., 1997; Halek and Eisenhauer, 2001; Kumar, 2009; Benjamin, Choi, and Fisher, 2013; Noussair et al, 2013). Institutional

[1] The two life insurance companies that received funds from TARP were the Hartford and Lincoln National. They obtained $3.4 billion and $950 million, respectively (Source: SNL Financial's TARP Participant List).

investors located in regions with a high Catholic-to-Protestant population ratio tend to hold more risky stocks and have more risky corporate policies (see, e.g., Kumar, Page, and Spalt, 2011; Schneider and Spalt, 2012, 2013). Similarly, Shu, Sulaeman, and Yeung (2012) document that mutual funds' risk-taking is impacted by local religious beliefs; mutual funds located in high-Catholic or low-Protestant ratio counties have a higher fund return volatility.

Although the risk-taking behaviors of insurance companies may be impacted by the local religious beliefs, market competition and economic incentives may diminish or even eliminate these cultural effects (Shu, Sulaeman, and Yeung, 2012, p. 1779). Especially in the highly regulated insurance industry where demand is sensitive to insurers' default risk (see, e.g., Doherty and Schlesinger, 1990; Cummins and Sommer, 1996; Cummins and Danzon, 1997) and regulators have the power to liquidate failing companies quickly (see, e.g., Cummins, Harrington, and Klein, 1995; DeAngelo, DeAngelo, and Gilson, 1996), market pressure may counterbalance any cultural influence on risk-taking decisions. Thus, whether local culture impacts risk-taking behaviors in insurance companies is an empirical question. Dissimilarity

In this paper, I empirically investigate the influence of local religious beliefs on insurance companies' risk-taking behaviors. Using data of U.S. single unaffiliated life insurance companies from 2001 to 2010, I examine the impact of county-level Catholic, Protestant, or Catholic-to-Protestant ratios on risk-taking behaviors of insurers headquartered in that county.[2] The Catholic (Protestant) ratio is measured as the fraction of population in a particular county that are

[2] In my study, I focus on Catholics and Protestants for the following reasons. First of all, Catholics and Protestants are the two largest religious denominations in the U.S. The recent American Religion Data Archive (ARDA) surveys do provide data on the numbers of adherents of other religious bodies. However, their fractions of adherents are so small that an empirical analysis on these religious beliefs may not produce reliable results. For example, the fraction of Jewish (Islamic, Orthodox) adherents to total county population has a mean of 0.277% (0.087%, 0.095%) and a median of 0% (0%, 0%) across the U.S. in 2000, respectively. In addition, Catholics and Protestants share many similarities in various aspects, and there are relatively limited differences (compared with Catholics vs. Muslims for instance). From my point of view, the differences in corporate risk-taking is the only obvious testable implication in context of financial institutions. See Benjamin, Choi, and Fisher (2013) for detailed dissimilarities between Catholics and Protestants.

Catholics (Protestants). The Catholic-to-Protestant ratio is defined as the Catholic ratio divided by the Protestant ratio.

I find that insurers that predominantly write annuities (annuity writers) are more common in regions with a larger fraction of Catholics in the population or a lower fraction of Protestants in the population.[3] Annuity writers are more risky than other types of life and health insurers as a result of their more volatile earnings and capitalization (Berry-Stölzle, Nini, and Wende, 2014). Therefore, this finding supports the notion that risky business is more accepted in high Catholic ratio or low Protestant ratio areas. In other words, my result is consistent with the theory that Catholics (Protestants) have a culture that is more (less) tolerant towards risks.

While most of the prior literature on insurer risk-taking focuses only on one risk proxy (Ho, Lai, and Lee, 2013), I employ three different risk measures to capture insurers' risk-taking activities.[4] Due to the systematic differences in risks taken between the insurers that predominately write annuity business (annuity writers/providers) and those that predominately write life business (life writers/providers) (Berry-Stölzle, Nini, and Wende, 2014), I separate the analyses on asset risk, investment risk, and total risk-taking decisions for these two major types of insurers with different business focuses. I document that annuity writers located in higher Catholic-to-Protestant ratio, higher Catholic ratio, or lower Protestant ratio counties take more asset risk and total risk. I also find that annuity writers' investment risk is significantly positively

[3] Insurers that predominantly write annuities are defined as insurers with over 2/3 of the net premiums written in ordinary individual annuity and group annuity business. They are referred as "annuity writers/providers" throughout the paper. Insurers that predominantly write life business are defined as insurers with over 2/3 of the net premiums written in industrial life, ordinary life, group life, and credit life insurance. They are referred as "life writers/providers" throughout the paper.

[4] I study asset risk, investment risk, and total risk, but not underwriting risk in this paper. Underwriting risk is usually captured by the volatility of loss ratio, and is commonly investigated in the property-casualty (P/C) insurance industry (see, e.g., Lamm-Tennant and Starks, 1993; Ho, Lai, and Lee, 2013). In the life insurance industry, an equivalent to the P/C loss ratio would be the ratio of life insurance output, incurred benefits (see, e.g., Cummins, Tennyson, and Weiss, 1999; Berger et al, 2000) to premiums earned. This ratio is relatively stable and the loss experience for life insurers is relatively smooth, due to the stable mortality rate and little exposure to catastrophic losses.

associated with the Catholic-to-Protestant ratio, and negatively associated with the Protestant ratio.

In addition to the main findings, I show evidence that insurers located in higher Catholic-to-Protestant ratio areas tend to have a longer history, larger net admitted assets, lower capital-to-assets ratio, and less reinsurance usage. In high Catholic-to-Protestant ratio areas, there are more insurance company headquarters, less stock insurers, more annuity providers, less life providers, and less publicly traded companies. With regard to the lines of business, insurers located in high Catholic-to-Protestant ratio areas tend to write more annuities, less life insurance, less accident and health business, and more other lines of business.

My study contributes to the literature in several ways. First, to the best of my knowledge, this research is the first to focus on the effects of religious beliefs, an important component of local culture, on risk-taking decisions of financial services firms. Given the fact that the risks taken by the financial services sector triggered the recent financial crisis, which spread over to other sectors and severely impacted the global economy, this study should be of interest to policymakers and regulators. Second, most extant studies on the effects of local religious beliefs only focus on publicly traded stock companies. I extend the literature by studying the impact of local religious beliefs on both private and public firms as well as different organizational forms. It is interesting to see that the conformity of firm behaviors with local culture still holds in private firms and firms with other organizational forms. In addition, I employ a variety of risk-taking measures and examine the insurers' risks from different aspects. Finally, whereas prior studies on the risk-taking of insurance industry concentrate on managerial ability, corporate governance, and firm characteristics, I make important contributions to the insurance literature by providing the first explanation from a local culture perspective.

The paper proceeds as follows. In the next section, I discuss related literature and conceptual background of my research design, and develop the hypothesis. Section 3 describes the sample, variable measurements, and methodology. Empirical results are presented in Section 4. The final section concludes.

2. Conceptual Background and Hypothesis Development

2.1 Theory for Relation between Religiosity and Risk-taking at Individual Level

Economists and Sociologists have disclosed a strong relationship between religion and economic behaviors at both macro and micro levels. Prior research provides evidence that religion plays an important role in government performance, creditor protection, economic development, and institutional structure (see, e.g., La Porta et al, 1999; Stulz and Williamson, 2003; Barro and McCleary, 2003; Guiso, Sapienza, and Zingales, 2003, 2006). On the other hand, recent financial studies have documented the association between religion and corporate investment, accounting policies, managerial decisions, and financial market outcomes (see, e.g., Hilary and Hui, 2009; Dyreng, Mayew, and Williams, 2012; McGuire, Omer, and Sharp, 2012; Kumar, Page, and Spalt, 2011). As suggested by Iannaccone (1998) and Noussair et al (2013), risk attitudes embedded in different religious beliefs could be one crucial mechanism that links religion and economic behaviors. Hence, it is important to recognize and examine the diverging risk attitudes of different religious beliefs (e.g., Catholics vs. Protestants), which allows one to gain insight into how religion shapes economic outcomes.

The distinct risk attitudes between Catholics and Protestants may root from their different viewpoints towards gambling (see, e.g., Kumar, Page, and Spalt, 2011; Benjamin, Choi, and Fisher, 2013). While Catholicism and Protestantism share many of the similar sacred texts, the moral teachings with regard to gambling are divergent (see, e.g., Halek and Eisenhauer, 2001; Shu, Sulaeman, and Yeung, 2012). Bell (1974) documents that it is prevalent in the U.S. that Protestantism morally condemns gambling, whereas Catholicism does not do so. The strong moral resistance to gambling and lotteries of Protestantism can be traced back to the inception of the Protestant movement, and it has been a fundamental doctrine of Protestantism. As a result, gambling is deemed as a sinful and reprehensible activity by typical Protestants (see, e.g., Starkey, 1964; Ozment, 1991; Ellison and Nybroten, 1999). In fact, the Southern Baptists, the largest Protestant denomination, have particularly strident opposition towards gambling (Kumar, Page, and Spalt, 2011). On the contrary, Catholicism preserves a tolerant view on and sometimes even promotes gambling. In many Catholic parishes, bingo and charitable gaming events based on gambling have been used frequently to raise funds (see, e.g., Diaz, 2000; Hoffman, 2000). Further, in southern Italy where Catholicism is popular, lotto players widely consider San Pantaleone as their patron saint. They also ask other saints and the spirits of the dead in purgatory to reveal the winning numbers for next draws (see, e.g., Fiorenza, 1897; Conte, 1910; Di Mauro, 1982; Binde, 2007). Prior literature has provided evidence that dominant local religious beliefs indeed drive the popularity of state lotteries (see, e.g., Berry and Berry, 1990; Martin and Yandle, 1990; Ellison and Nybroten, 1999). A number of recent studies also empirically show that Catholic and Protestant norms towards gambling extend to financial decisions (see, e.g., Kumar, 2009; Doran, Jiang, and Peterson, 2012). Gambling has a possibility to either gain or lose financially. From this perspective, gambling is analogous to taking financial risk. Since Catholics are more tolerant to gambling than Protestants, I would expect Catholics to be more open towards risk-taking or less risk-averse than Protestants.

In addition, Noussair et al. (2013) provide evidence that the correlation between religion and risk preferences is not driven by religious beliefs per se, but by the social and institutional aspects of church membership. Consistent with this view, a few studies argue that the exogenous and unobserved factors that affect behaviors also contribute to the causal effect of religion on risk attitudes (see, e.g., Lillard and Price, 2007; Benjamin, Choi, and Fisher, 2013). Therefore, examining the social effects of attendance in church activities may also provide possible explanation for the differing risk attitudes between Catholics and Protestants. Using a representative sample of paid survey participants, Noussair et al. (2013) find that the fraction of Protestants who actively attend church activities is greater than that of Catholics, and Protestants pray more frequently than Catholics. They also document that Protestants hold stronger religious beliefs on average. A few studies tie active church participation with higher degree of risk aversion, since risk-averse individuals are more likely to seek relief and comfort via church attendance (see, e.g., Gasper and Clore, 1998; Hilary and Hui, 2009; Shu, Sulaeman, and Yeung, 2012). Hence, through the link between risk attitudes and intensity of church involvement, I also expect Catholics to be more risk-tolerant or less risk-averse than Protestants.

2.2 Individual Characteristics and Firm Behavior

The characteristics of individuals working in an institution are likely to be congruent with the corporate culture. According to social identity theories (see, e.g., Tajfel, 1978; Hogg and Abrams, 1988), people derive their personal identity from social group membership, such as ethnicity, gender, nationality, religion, occupation, and etc. Individuals' behaviors are to a large extent shaped by adopting and internalizing the values, norms, and attributes of their groups. Therefore, people tend to adjust their behaviors to adapt to the dominant values and principles of groups. This tendency has implications for firm decision. Personnel psychology literature builds the link between individual and organizational characteristics. Schneider (1987) suggests that a firm yields a particular type of employees not by chance. It is through a process of attraction to and selection by the firm, as well as natural attrition. The employees' behaviors, in turn, form the firm's culture and determine corporate decisions. Schneider, Goldstein, and Smith (1995) provide a detailed review of empirical evidence supporting this theory.

Further, employees and managers choose to join a firm with a culture they feel comfortable with. Several empirical studies as follows provide evidence confirming the argument. Vroom (1966) finds that individuals select the workplace that is the most helpful in obtaining their valued outcomes. Tom (1971) and Holland (1976) show that people desire working environments with compatible personality profile. Using a sample of 65 CEOs who changed firms from 1991 to 2003, Hilary and Hui (2009) find that when switching employers CEOs are more likely to join a firm with a similar religious environment as their previous employer. Their results are robust to four specifications, including ones that control for local demographic variables of both previous and current firm headquarter regions, an array of CEO personal characteristics, and their motivating reasons of departure. Based on the above two reasons and related empirical evidence, I argue that corporate culture is consistent with the characteristics of employees, including CEOs.

In addition, Kumar, Page, and Spalt (2011) argue that, as one key aspect of local culture, dominant local religion systematically influences the behaviors of local individuals, even though they do not personally follow the prevailing local belief. In other words, individual characteristics are compatible with the local culture. Based on the consistency of individual characteristics and corporate culture developed earlier, I expect individual characteristics, corporate culture, and local culture to be congruent with each other. Consistent with this view, Hilary and Hui (2009) also claim that it is natural to expect the corporate culture to be aligned with the institution's local environment.

2.3 Previous Evidence on Religiosity and Risk-taking at Individual and Institutional Levels

A bulk of surveys and empirical studies produce results supporting that individual Catholics and institutions headquartered in high Catholic ratio areas generally exhibit more tolerance towards risk-taking or less risk-aversion than individual Protestants and institutions headquartered in high Protestant ratio areas. Barsky et al. (1997) utilize the survey data among the participants in the Health and Retirement Study (HRS) to elicit their risk-aversion information. The hypothetical question asking their willingness to gamble on life-time income indicates that Catholics are less risk averse than Protestants. Employing the same data source but different methodologies, Halek and Eisenhauer (2001) find consistent results. Through a designed lottery game that involves real stakes, Noussair et al. (2013) find that individual Catholics are less risk-averse than individual Protestants. Other than questionnaires and experiments, Catholics take part more intensively in lotteries than Protestants in real-life (see, e.g., Tec, 1964; Grichting, 1986). In addition, Catholic individual investors prefer stocks with lottery features more than Protestant individuals (Kumar, 2009). Evidence is found not only at the individual's level, but also at the business entity's level. Institutional investors located in U.S. counties with a higher Catholic-to-Protestant ratio are more likely to hold risky investments (Kumar, Page, and Spalt, 2011), and have higher investment return volatility as well as idiosyncratic volatility (Shu, Sulaeman, and Yeung, 2012).[5] Moreover, firms headquartered in

[5] Kumar, Page, and Spalt (2011) also find that institutional investors located in the U.S. counties with a higher Catholic (Protestant) ratio are more (less) likely to hold risky investments. Similarly, Shu, Sulaeman, and Yeung

higher Catholic-to-Protestant ratio regions take long shots to allocate more capital to divisions with greatly skewed expected returns (Schneider and Spalt, 2012), and acquire more lottery-type targets with negative net present values in corporate acquisitions (Schneider and Spalt, 2013). In addition, companies located in higher Catholic (Protestant) ratio counties are more (less) likely to display aggressive corporate behaviors in terms of excessive compensation package grants to their managers and opportunistic earnings management practice (Grullon, Kanatas, and Weston, 2010).

Given the theory and empirical evidence on the relationship between local religious beliefs and risk in the literature, I formulate the following testable hypothesis:

> ***Hypothesis*: *Insurance companies located in high Catholic or low Protestant ratio areas take more risks.***

3. Data and Methodology

3.1 Sample Selection

In the insurance industry, there are single unaffiliated firms and insurance groups. Insurance groups consist of multiple affiliated subsidiaries, which may be domiciled in various locations across the country. Then it is difficult to determine the local culture of which subsidiary dominantly impacts the group level decisions. Even if the religious beliefs in the group headquarter may have the primary effects, they might be diluted or dissolved by the conflicting beliefs at the subsidiary level. On the contrary, single unaffiliated insurers operate at a single location. Hence, their headquarters' local culture should have a measurable influence on corporate decisions. In addition, single unaffiliated insurers tend to be smaller than the group

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(2012) find that mutual funds in higher Catholic (Protestant) ratio counties have higher (lower) investment return volatility and idiosyncratic volatility.

insurers. Hence, they may have greater latitude in their corporate decisions, and the risk attitudes of local clientele are more likely to influence their decisions since their customer base may primarily be local (Kumar, Page, and Spalt, 2011). Similar arguments are present in the extant literature. Baker, Bradley, and Wurgler (2011) claim that the systematic differences between large group institutions and other institutions exist, which include customer base, geographic office diversification, investment processes, and standardized benchmarking practices. Based on these differences, Kumar, Page, and Spalt (2011) argue that religious beliefs would only influence small and moderate-sized institutions without the complex group-subsidiary structure, and they empirically support the speculation in their study. In the same vein, I focus my analysis on single unaffiliated insurance companies.

The initial sample consists of all U.S. single unaffiliated life insurance companies in the *Best's Annual Statement File, Life-Health Edition* from 2001 to 2010. For some of the risk-taking measures, I need to compute the standard deviations of certain financial statement variables for the past 4 years. Hence, the year for which all the variables for regression analyses are available starts from 2004. I apply several sample screening procedures as follows. First, following Berry-Stölzle, Nini, and Wende (2014), I eliminate the insurers that do not primarily write life insurance (life writers) or predominantly write annuities (annuity writers). Life writers are defined as the insurers with over two-thirds of net premiums written in life lines of business, and annuity writers are defined as those with over two-thirds of net premiums written in annuity lines of business.[6] As a result, accident and health insurers are removed from the sample. I then drop the firms predominantly operating as reinsurers. Specifically, I exclude observations if the

[6] I collect net premiums written from the "Analysis of operations by line of business" page of *Best's Annual Statement File, Life-Health Edition* as the sum of lines "1 Premiums and annuity considerations for life and accident and health contracts" and "2 Considerations for supplementary contracts with life contingencies." The portion of annuity business is based on the sum of premiums in individual and group annuities. The portion of life business is calculated as the sum of industrial life, ordinary life, group life, and credit life.

ratio of reinsurance assumed to the sum of direct premiums written and reinsurance assumed (reinsurance business fraction) has a value above 50%. These screenings leave me with 763 observations or 221 unique insurers. Next, I remove firm-year observations with missing or non-positive total assets, surplus, or net premiums written. In addition, I drop insurers with strange reinsurance arrangements. In particular, insurers with a negative reinsurance business fraction are removed. My final sample comprises 705 firm-year observations or 202 single unaffiliated life insurers for the period of 2004 to 2010. Table 1 reports the number of observations for each step of sample selection process.

3.2 Religiosity Ratios

The data on local religious beliefs is available from the American Religion Data Archive (ARDA), which is jointly sponsored by the Association of Statisticians of American Religious Bodies and the Glenmary Research Center. ARDA data are based on a series of surveys that are conducted approximately every 10 years. Each survey provides the number of congregations and adherents of Judeo-Christian church bodies in each county. In this study, I utilize the survey conducted in 2000 and 2010, and the numbers of religious groups included are 149 and 236, respectively. Following the prior literature (see, e.g., Hilary and Hui, 2009; Shu, Sulaeman, and Yeung, 2012), I calculate the *Protestant Ratio* (*Catholic Ratio*) of each county. The *Protestant Ratio* (*Catholic Ratio*) is defined as the numbers of adherents of Protestant denominations (Catholic denominations) within the county divided by the county's total population. Following Kumar, Page, and Spalt (2011), I also define the *Catholic-to-Protestant Ratio* to capture the relative fractions of Catholics and Protestants in a county. It provides a measure for the sharpest comparison on the risk-taking between Catholics and Protestants. My sample spans from 2004 to

2010, among which the religiosity ratios of the survey year 2010 are computed directly. For the non-survey years from 2004 to 2009, I linearly interpolate the religion data in 2000 and 2010 to obtain the values.

To match the county-level religiosity ratios with insurance companies' financial statement data, I first collect the zip code of the corporate administrative office address from *Best's Insurance Reports, Life-Health Edition*. Then I obtain the county location for each insurer by matching the zip code with the corresponding county using the geographic file from the SAS data library. Finally, I assign the county's religiosity ratios to the insurer located in that county.

3.3 Risk-Taking Measures

A variety of risk-taking measures are used in the finance and insurance literature. Shu, Sulaeman, and Yeung (2012) employ the standard deviation of monthly fund returns during the year to measure mutual funds' risk-taking. Kumar, Page, and Spalt (2011) use firms' holding of stocks with lottery-type characteristics to proxy for risk preference. John, Litov, and Yeung (2008) use the firm earnings volatility calculated as the standard deviation of the difference of a firm's ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) to assets from the country average.

In the insurance literature, Lee, Mayers, and Smith (1997) analyze changes in insurance companies' portfolio composition. Assuming investments in stocks are riskier than in bonds, they interpret an increase in stock holdings and decrease in bond holdings in an insurer's portfolio as evidence for increased risk-taking. Some studies (see, e.g., Cummins and Harrington, 1988; Downs and Sommer, 1999; Pottier and Xu, 2013) focus on stock insurers and construct market risk-taking measures based on the Capital Asset Pricing Model (CAPM). For insurance-specific operations, previous proxies for risk-taking behaviors include the variance of the loss ratio (Lamm-Tennant and Starks, 1993), and the coefficient of variation (CV) of underwriting leverage and the CV of solvency ratio for cross-country analyses (Fields, Gupta, Prakash, 2012). However, most of these previous studies on insurer risk-taking only examine one type of risk. Ho, Lai, and Lee (2013) advocate that in order to capture the risks taken by insurers thoroughly, multiple measures need to be used. Hence, I employ a high risk indicator, and three different measures to gauge different aspects of risk-taking for life insurance companies.

Berry-Stölzle, Nini, and Wende (2014) provide evidence that insurers that predominately write annuities have substantially more volatile earnings and capitalization levels than other life and health insurers. Thus, I employ an annuity writer dummy variable to indicate a relatively high level of risk in terms of business model. I expect that insurers in high Catholic ratio or low Protestant ratio areas are more likely to be annuity writers, if Catholics are less risk-averse than Protestants.

An insurer's investment portfolio consists of various types of assets, and the riskiness of each category of investment varies. For example, stocks and real estates are relatively high-risk investments, compared to fixed income securities, cash, and short-term investments (see, e.g., Lee, Mayers, and Smith, 1997; Ibbotson Associates, 1999). Therefore, the relative weight of the risky assets in the insurer's investment portfolio affects its insolvency risk. Following the literature (see, e.g., Gaver and Pottier, 2005), I compute the ratio of investments in equity securities and real estate to cash and total investments to capture asset risk.

In order to measure the investment risk of an insurer, following Ho, Lai, and Lee (2013), I use the standard deviations of the insurance company's returns on investment (ROI). The ROI is defined as the ratio of investment income plus realized capital gains to cash and invested assets. The standard deviations are computed based on a four-year rolling window.

Lastly, I use the standard deviations of the insurance company's returns on assets (ROA) to measure the overall risk for shareholders or policyholders. According to Ho, Lai, and Lee (2013), this total risk reflects the combination of all the aspects of risks taken by insurers, and determines insurers' risk profile. I define ROA as the ratio of net income to total net admitted assets. The standard deviations are computed based on a four-year rolling window. Insurer financial statement data are obtained from *Best's Annual Statement File, Life-Health Edition*.

3.4 Model Specification

As discussed in Section 3.3, annuity writers have more volatile earnings and capitalization. If Catholics (Protestants) are more (less) tolerant towards risks, I would expect annuity writers to be more (less) likely to be headquartered in high Catholic (Protestant) ratio regions. To test this prediction, I estimate a multi-period Logit regression of an annuity writer indicator on local religiosity ratios and various county-level demographic characteristics:

$$Annuity\ Writer_{i,t} = \alpha_0 + \alpha_1 ReligiosityRatio_{i,t} + \alpha^j Demo_{j,i,t} + \alpha^l Year_{l,i,t} + u_{i,t}, \tag{1}$$

where *Annuity Writer* is a dummy variable that takes a value of one if insurer *i* has more than two-thirds of the total net premiums written in annuity lines of business in year *t*, and zero otherwise. *ReligiosityRatio* includes the three religiosity variables, namely *Catholic-to-Protestant Ratio*, *Catholic Ratio*, and *Protestant Ratio*, where I use only one of them at a time in each regression.[7] *Demo* is a vector consisting of demographic variables—*Age*, *Education*,

[7] When using *Catholic-to-Protestant Ratio* as the religiosity variable, the model does not control for the total religiousness of insurers' headquarter counties. For example, County A with a *Catholic Ratio* and a *Protestant Ratio* of both 5% and County B with both 40% have the same *Catholic-to-Protestant Ratio* of 1. But the total religiousness

Income, *Population*, *Minority*, *Married*, *MaletoFemale*, and *Population Density*. Year fixed effects are included, and u is the error term. I control for county-level demographic variables to ensure that the impacts attributed to religion truly reveal the effects of the predominant local religion, as opposed to other socioeconomic aspects that may be correlated with religious beliefs. I also report two-way robust standard errors clustered by firm and by year.[8]

Next, I investigate the effects of local religious beliefs on insurers' risk-taking behaviors, controlling for both firm-level and county-level characteristics. The model specification is as follows:

$$Risk\text{-}taking_{i,\,t} = \alpha_0 + \alpha_1 ReligiosityRatio_{i,\,t} + \alpha^j Insurer_{j,\,i,\,t} + \alpha^k Demo_{k,\,i,\,t} + \alpha^l Year_{l,\,i,\,t} + u_{i,\,t}\,, \tag{2}$$

where *Risk-taking* represents the three risk measures defined earlier: asset risk, investment risk, and total risk for insurer i in year t. *ReligiosityRatio* stands for the three religiosity measures, namely *Catholic-to-Protestant Ratio*, *Catholic Ratio*, and *Protestant Ratio*. I expect that the *Catholic-to-Protestant Ratio* and *Catholic Ratio* to be positively associated and *Protestant Ratio* to be negatively related to the risk-taking measures. *Insurer* is a vector of firm-level control variables including firm size, capital-to-assets ratio, net premium growth, reinsurance use, geographic Herfindahl–Hirschman Index (HHI), as well as indicator variables of mutual insurer, stock insurer, annuity writer, life writer, and publicly traded insurer. *Demo* is a vector of county-level demographic characteristics including *Age*, *Education*, *Income*, *Population*, *Minority*, *Married*, *MaletoFemale*, and *Population Density*. The model also includes year fixed effects to

of County A (assuming only Catholics and Protestants for simplicity) is 10%, whereas County B is 80%. In order to address this concern, I check the variation of total religiosity ratios (total number of religious adherents divided by the total population of a county) across counties, and find that it is relatively small (with the 25 percentile, median, and 75 percentile 0.492, 0.564, and 0.635, respectively). Further, when examining *Catholic-to-Protestant Ratio*, the models are robust to adding the total religiosity ratio as an additional control variable when regressing on the annuity writer indicator and all risk-taking measures.

[8] The results are robust to using two-way standard errors corrected for county clustering and year clustering.

control for potential heterogeneity in risk-taking behaviors over time. Finally, *u* is the error term. I use a Tobit model with upper and lower bounds and one-way robust standard errors corrected for firm-level clustering to study asset risk-taking.[9] Regressions on investment risk and total risk are estimated using pooled ordinary least square (*OLS*) with standard errors corrected for two-way clustering by firm and by year.[10] I perform regressions separately on asset risk, investment risk, and total risk for all sample insurers, insurers that primarily write annuities, and those that primarily write life business, respectively.

I control for firm-specific characteristics as well as for demographic differences across counties. The selection of firm-level control variables are based on recent empirical studies (see, e.g., Carson and Hoyt, 1995; Browne, Carson, and Hoyt, 2001; Pottier, 2011; Berry-Stölzle, Nini, and Wende, 2014), and they are described as follows. I include firm size as measured by the natural logarithm of total net admitted assets. Capital-to-assets ratio is calculated as the fraction of total capital and surplus to total net admitted assets. Net premium growth is measured as the change of net premiums written from the previous year divided by the previous year's net premiums written. Reinsurance use is constructed as the percentage of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. Since the reinsurance use ratio outside the range of 0 and 1 are unreasonable, I winsorize the ratio at 0 and 1. Geographic HHI is measured as $\Sigma\ (DB_i\ /\ TDB)^2$, where DB_i is the value of total direct premiums and annuity considerations in state *i*, and *TDB* is the insurer's total direct premiums and annuity

[9] Since the asset risk is calculated as ratios, and is bounded between 0 and 1, it is more appropriate to use Tobit regressions to model asset risk as a dependent variable. In the pooled OLS models for investment risk and total risk, I report two-way robust standard errors corrected for clustering by firm and by year. To be consistent, I would prefer a Tobit model with upper and lower bounds and two-way robust standard errors as well. However, such a Tobit model does not seem to exist yet. Therefore, I use a Tobit model with upper and lower bounds and one-way robust standard errors corrected for firm-level clustering to study insurer asset risk-taking behaviors.

[10] Shu, Sulaeman, and Yeung (2012) report the standard errors that are corrected for two-way clustering by county and by year. As a robustness check, I also correct standard errors for the two-way clustering by county and by year, and the results are very similar.

considerations across the U.S. In order to control for heterogeneities in risk-taking that might arise from differences across organizational forms, I include the mutual and stock insurer dummy variables, and the omitted category are other organizational forms. The annuity writer or life writer indicator is also added to address the distinct risk-taking behaviors due to the different business models for insurers that primarily write annuity business and those that primarily write life business. In addition, I include an indicator of whether an insurer is publicly traded to control for the differences in risk-taking between the public and private insurers.

I obtain the county-level demographic data from the U.S. Census Bureau, which include the median age of the county population (*Age*), the fraction of highly educated people (bachelor's degree or higher) among the population 25 years or older (*Education*), the per capita personal income (*Income*), the county's total population (*Population*), the fraction of the minority population that is not White alone, non-Hispanic (*Minority*), the ratio of married households to the total number of households (*Married*), the ratio of the male population to the female population (*MaletoFemale*), and the total population of a county divided by the county's size of area (*Population Density*).

4. Results

4.1 Descriptive Statistics

Table 2 displays summary statistics for the variables used in this study. All monetary values are inflation adjusted and converted to constant 2000 US dollars. The results indicate that a typical single unaffiliated insurance company in my sample is located in a county with 19.38% Catholic population and 22.04% Protestant population, which makes the county Catholic-to-Protestant ratio 0.893. However, the Catholic-to-Protestant ratio of a typical county across the

U.S. is 0.253, with 8.31% Catholics and 35.05% Protestants. This is because that my sample insurers (and insurance companies in general) are clustered in regions with relatively dense Catholic populations; the cities with the most sample insurers include Chicago, Cincinnati, New York City, and Dallas. Nevertheless, there are also substantial variations in local religious beliefs in my sample. As demonstrated in Table 2, the 75th percentile of *Catholic-to-Protestant Ratio* (2.018) is more than 6 times of the 25th percentile (0.326); I observe the similar pattern with the *Catholic Ratio* and *Protestant Ratio*, respectively. In addition, my insurer sample exhibits a significant geographic dispersion. The number of sample insurers varies from year to year, and the average number for the 7-year sample period is 100.714.[11] Untabulated results reveal that these insurers are spread out in 42 states or 75 counties, and the states with the highest insurer concentrations are Texas (9.36% of sample), Pennsylvania (8.79% of sample), Illinois (8.09% of sample), Ohio (6.67% of sample), New York (6.24% of sample), and Louisiana (5.11% of sample).

As the proxy for asset risk, stock and real estate investment fraction for an average sample insurer is 7.20%. In order to gauge the *Investment Risk* and *Total Risk*, I need to calculate the standard deviations of certain accounting measures for the past 4 years. Thus the number of observations for these two risk measures is lower than for the other variables. A typical sample insurer has a volatility of ROI of 0.005 and a volatility of ROA of 0.006. There are wide variations in these two risk measures. For example, the 75th percentile for ROA volatility is 0.012, three time larger than the 25th percentile of 0.003. The similar pattern is observed for ROI volatility as well.

[11] More specifically, there are 107 single unaffiliated insurers in my sample in 2004, 104 in 2005, 102 in 2006, 97 in 2007, 87 in 2008, 88 in 2009, and 120 in 2010.

The average total assets across the sample insurers is 102.462 million dollars ($e^{18.445}$), which indicates that my sample is comprised of small and moderate-sized firms. They are expected to be more susceptible to local religions than large firms (Kumar, Page, and Spalt, 2011). A typical sample insurer has a capital-to-asset ratio of 13.67%, net premium growth of -1.84%, reinsurance use of 4.72%, and geographic HHI of 0.312. In my sample, there are 11.20% of mutual insurers and 70.49% of stock insurers. 26.10% of the sample are predominate life insurance writers and 73.90% are annuity writers. In addition, 4.97% of the sample are publicly traded firms, with the majority of sample being private firms. On average life insurance consists of 68.44% of the business of sample insurance companies, annuities account for 27.77% (with the breakdown between the two major components as 25.74% for ordinary individual annuity and 2.03% for group annuity), Accident & Health makes up 3.37%, and other business has a share of 0.43%. The insurers in my sample have fairly long histories, with the average age being 67.586 years

4.2 Sorting Results Based on Religiosity Ratios

I form quintile portfolios of insurers sorted on each of my religiosity ratios, and calculate the means of the firm characteristics for each quintile. I report the differences between the highest and lowest quintiles, and the associated *p*-value and *t*-statistics. By definition, however, the numbers of firm-year observations are the same for each quintile. Thus in order to get an idea whether there are more insurers in high Catholic-ratio or high Protestant-ratio areas, I employ a different sorting procedure. For each year during 2004-2010, I sort the headquarter counties of sample insurers into quintiles based on their religiosity ratios, then count the number of insurers in each quintile, and report the time-series means for each quintile. Table 3 exhibits the mean firm-level variables sorted on religiosity ratios. Panel A of the univariate analysis does not show a significant relationship between *Catholic-to-Protestant Ratio* and asset risk, investment risk, or total risk measure. Additionally, the results document that larger and older firms, and firms with lower capital-to-asset ratio, less reinsurance use, smaller geographic HHI, less life insurance business, less Accident & Health business, and more other business locate in higher *Catholic-to-protestant Ratio* areas. Furthermore, more annuity writers, and less stock insurers, life writers, and publicly traded insurers are headquartered in higher *Catholic-to-protestant Ratio* areas. The results demonstrate that insurers' fraction of annuity business increases with *Catholic-to-Protestant Ratio*. The spread between the top and the bottom quintiles is 21.3% and is significant at 1% level. The same pattern is observed for the two components of the annuity business—ordinary annuity and group annuity business fractions. The results are consistent with the findings documented by Berry-Stölzle, Nini, and Wende (2014) that annuity writers are more risky than life writers, which reflects the higher riskiness level of annuity business than the other lines of life and health insurance. With regard to the other lines of business breakdown, I find that insurers that write more supplementary contracts and group Accident & Health business, and less credit life, Accident & Health credit, and Accident & Health other business tend to be headquartered in higher *Catholic-to-protestant Ratio* regions. Lastly, there are simply more insurers in high *Catholic-to-protestant Ratio* counties.

Panel B of Table 3 reports the firm-level variables sorted on *Catholic Ratio*. I still find no significant links between *Catholic Ratio and* asset risk as well as total risk. However, there is weak evidence that insurers located in higher *Catholic Ratio* counties take less investment risk (*p*-value = 0.093), which contradicts my hypothesis. However, there is a small variation of *Investment Risk* among the 5 quintiles (ranging from 0.006 to 0.009). Further, the univariate test does not control for other factors that may also influence risk-taking. Thus, one cannot make a conclusion on the relation between religion and investment risk-taking (or other risk-taking behaviors) unless the multivariate analyses are conducted. In addition, I find that larger and older firms, and firms with less capital-to-asset ratio, higher net premium growth, less reinsurance use, and smaller geographic HHI are headquartered in high *Catholic Ratio* areas. Moreover, more mutual insurers and annuity writers, and less stock insurers, life writers, and publicly traded firms locate in high *Catholic Ratio* counties. Consistent with the results in Panel A, I find a positive relation between insurers' annuity business fraction and local *Catholic Ratio*. The difference between the highest and the lowest quintiles is 25.7% and is significant at 1% level. In terms of other business lines, insures with more *Other Bus. Fraction,* and less *Life Bus. Fraction* and *A&H Bus. Fraction* are located in high *Catholic Ratio* counties. Further, more insurers are clustered in high *Catholic Ratio* regions.

Panel C of Table 3 exhibits the firm-level variables sorted on *Protestant Ratio*. The results show that smaller and younger firms, and firms that reinsure more and are more geographically concentrated tend to locate in areas with dense Protestant population. Also, more stock insurers and life writers, and less mutual insurers, and annuity writers are headquartered in high *Protestant Ratio* regions. Further, I find evidence that insurers have significantly less annuity business in high *Protestant Ratio* regions. The spread between the highest and the lowest quintiles is 17.3% and is significant at 1% level. In addition, insurers headquartered in higher *Protestant Ratio* counties tend to have higher *Life Bus. Fraction*, *A&H Bus. Fraction*, and lower *Other Bus. Fraction*. Finally, there are few insurers in high *Protestant Ratio* areas.

4.3 Regression Analyses of Risk-taking

Insurers that predominantly write annuities have more volatile earnings and capitalization than other types of life and health insurance writers (Berry-Stölzle, Nini, and Wende, 2014). In other words, they are more risky. Based on the risk attitudes of Catholics and Protestants, I expect that annuity writers are more likely to locate in areas with high Catholic (low Protestant) population. To investigate whether annuity writers are more common in Catholics or Protestants denominated counties, I estimate a multi-period Logit regression of annuity writer dummy with year fixed-effects on various county-level demographic characteristics, including local religious beliefs. The standard errors are corrected for two-way clustering by firm and by year. As reported in Table 4, the results show that annuity writers are more commonly seen in counties with higher concentration of Catholics or lower concentration of Protestants. I also find that annuity writers are more likely to be located in counties with older population and lower per capita income. This may represent the higher need for annuity products by elderly and low income residents. Furthermore, population density is positively related to the likelihood of being the headquarter county of annuity writers. The higher the population density, the more urbanized an area is. Hence, the population density can be regarded as a proxy for urbanization. The result shows that annuity writers are more common in urban areas. This may due to the fact that there is a larger client base and therefore larger demand in these regions.

I further run regressions of multiple risk-taking measures from various aspects that control for a broad set of insurer characteristics and county-level demographic variables. In order to improve readability of the coefficients of the explanatory variables, the dependent variables are multiplied by 100 in all multivariate models.

Table 5 reports the regression results on asset risk-taking. The models in the first three columns are performed for the full sample of insurers. Even though the signs are as expected for the three religiosity ratios, the coefficients are not significant. Due to the systematic differences in risk-taking behaviors between insurers that primarily write annuities and those that primarily write life business, I separate the analysis for these two major types of insurers with diverse business concentrations. The middle three columns report the findings for annuity writers. Consistent with my hypothesis, the results show that the *Catholic-to-Protestant Ratio* and *Catholic Ratio* of annuity providers' headquarter counties are positively associated with their asset risk, as measured by the ratio of investments in equity securities and real estate to cash and total investments. The *Protestant Ratio* of annuity writers' headquarter counties is negatively associated with their asset risk. Additionally, smaller annuity insurers, and those with less net premium growth, reinsurance use, and geographic concentration take more asset risk. Mutuals take more asset risk than the omitted category of insurers (insurers with other organizational forms than stock or mutual). I do not find evidence that religion affects asset risk-taking for life writers.

The results of insurers' investment risk-taking behaviors are exhibited in Table 6. I again separate my regression analysis for the full sample of firms, annuity providers, and life providers. I do not find significant effects of local religion on all insurers in general. However, given the systematic differences between annuity writers and life writers, the religion impacts on these two insurer types may offset each other. When focusing on annuity providers, I find those located in high *Catholic-to-Protestant Ratio* or low *Protestant Ratio* counties take more investment risk, captured by the standard deviations of firm's ratio of investment income plus realized capital gains to the total invested net admitted assets (ROI) for the past 4 years. In general, annuity writers with higher capital-to-assets ratio take more investment risk. Stock insurers take more investment risk than mutuals and insurers with other organizational forms. I do not find evidence that religion affects investment risk-taking for life writers.

Table 7 reports the results of total risk-taking on religiosity ratios as well as firm and county characteristics. When focusing on insurers that predominantly write annuities, I find those located in high *Catholic-to-Protestant Ratio*, high *Catholic Ratio*, or low *Protestant Ratio* counties take more total risk, measured by the standard deviations of firm's ratio of net income to the total net admitted assets (ROA) for the past 4 years. This risk measure encompasses various aspects of risk sources and represents the most important overall risk for shareholders or policyholders (Ho, Lai, and Lee, 2013). The findings indicate that stock annuity insurers take significantly more total risk than mutual and other types of insurers, which is consistent with the prior literature (see, e.g., Mayers and Smith, 1981, 1986). In addition, across all 9 columns of regressions, I find consistent and significant results that single unaffiliated insurers (including both annuity writers and life writers) with higher capital-to-assets ratio and net premium growth take more total risk. Higher capital-to-assets ratio may provide an insurer larger cushion to absorb potential losses caused by total risk-taking; higher net premium growth is usually associated with greater growth opportunities, which may lead to higher uncertainty in firm's ROA. Lastly, the adjusted R-squares on three measures of religiosity ratios for annuity providers range from 0.819 to 0.837. It demonstrates that the models explain the majority of the variations in insurers' total risk-taking activities. I do not observe the influence of religion on the full sample of insurers and life provider subsample.

In addition to *Catholic Ratio* and *Protestant Ratio*, I collect the number of adherents for the two groups of Mainline Protestant and Evangelical Protestants separately from the American

Religion Data Archive (ARDA). I then construct two new variables: the *Mainline Ratio* and the *Evangelical Ratio*. The *Mainline* (*Evangelical*) *Ratio* is calculated as the fraction of the population in a particular county that is affiliated with Mainline (Evangelical) Protestant churches. I use these two additional religiosity ratios to study whether annuity writers are less likely to be headquartered in high *Mainline* (*Evangelical*) *Ratio* areas, and whether local Mainline (Evangelical) belief affects insurers' risk-taking behaviors. Untabulated results show that annuity writers are less common in both high *Mainline Ratio* and high *Evangelical Ratio* areas. The magnitude of coefficient on *Evangelical Ratio* is smaller than that of *Mainline Ratio* (-3.969 vs. -7.629). With regard to whether the Mainline (Evangelical) belief affects insurers' risk-taking decisions, for annuity writers *Evangelical Ratio* is significantly negatively related to asset risk and investment risk, while *Mainline Ratio* is insignificant. The coefficient magnitude of *Evangelical Ratio* is larger than *Protestant Ratio* in both cases. For total risk of annuity writers, both the *Evangelical Ratio* and the *Mainline Ratio* are negative and significant. Overall the effect of the *Evangelical Ratio* on insurers' risk-taking behaviors is stronger than the effect of the *Mainline Ratio*. In other words, the effects of the local Protestant belief are mainly driven by the Evangelical belief.

4.4 Robustness Checks

Some insurance companies are affiliated with certain religious groups, and use a targeted marketing strategy to focus on certain religious clientele with organization memberships. In order to ensure my results are not driven by such a specific type of insurers, I examine all 202 insurance companies in my sample and identify 12 insurers with religious words in their names. First, I dropped these 12 firms, or 49 observations from my sample, and re-run all regressions.

Overall the results (untabulated) are qualitatively the same as in my baseline model, if not stronger. Alternatively, I coded a dummy variable (*Indicator: Targeted Religious Clientele*) that equals to one for these 12 firms, and zero otherwise. I add the *Indicator: Targeted Religious Clientele* to the baseline model, and rerun all regressions. The results (untabulated) are robust to adding this dummy variable.

As another robustness check, I collect the fraction of Hispanics in the county population from the U.S. Census database, and construct the *Hispanic* county demographic control variable. I add the *Hispanic* as an additional control variable in all regression models. Overall the results (untabulated) are stronger with more significant religiosity ratios and higher significance levels.

Additionally, in order to check if there are any influential years that drive the results, I drop one year at a time (from 2004 to 2010) from my sample and rerun all the regressions. In general, the results (untabulated) are robust to dropping any year of the sample period.

5. Conclusions

The recent financial crisis has driven a great deal of attention in the risk-taking behaviors of the financial services sector from various parties, including researchers. There is also an increasing interest in academia on behavioral and cultural aspects of business decisions. The goal of this study is to investigate the intersection of these two growing strands of literature. In particular, I examine the effects of local religious beliefs, a key aspect of local culture, on the corporate risk-taking behaviors of insurance companies, an important player in the financial services sector. Previous literature has documented that local religious beliefs indeed impact corporate investments, earnings management, tax avoidance, and manager option grants and compensation package, as well as investment decisions of mutual funds. However, little evidence has been shown among the financial institutions. Given their special role in the recent financial crisis and the highly regulated environment, as well as the strong market disciplines, a separate study of the religion aspect of risk-taking decisions in financial institutions is warranted.

In this paper, I examine the influence of local religious beliefs on insurance companies' risk-taking behaviors. Using the sample of U.S. single unaffiliated life insurance companies from 2001 to 2010, I study the impact of county-level Catholic or Protestant ratios, measured by the share of Catholic or Protestant adherents to the total population of a county, as well as Catholic-to-Protestant ratio on risk-taking decisions of insurers headquartered in that county. First of all, I find that insurers that predominantly write annuities, more risky than the insurers with other business concentrations, are more common in regions with a larger Catholic or a smaller Protestant population, controlling for an array of county-level demographic characteristics and two-way clustering by firm and by year. I then employ three different risk measures to capture insurers' risk-taking activities from various aspects. In recognition of the systematic difference in risks taken between the insurers that predominately write annuity business and those that predominately write life business, I separate the analyses for them on asset risk, investment risk, and total risk-taking decisions. I document that annuity writers located in high Catholic-to-Protestant ratio, high Catholic ratio, or low Protestant ratio counties take more asset risk and total risk. I also find that annuity writers' investment risk is negatively related with their headquarter county's Protestant ratio. I do not find evidence on these risk-taking behaviors for insurers that predominantly write life business. My findings are consistent with prior theories and empirical evidence regarding the links between religions and risk attitudes. My study demonstrates that, despite the stringent regulation, intense competition, and strong market discipline within the insurance industry, the effects of local culture on insurer behaviors are not negligible.

My study provides the first evidence that local religious beliefs, an important aspect of local culture, noticeably affect financial institutions' behavior. This should be of interest to policymakers, regulators, and researchers, especially after the recent financial crisis. Further, whereas prior research on religion impacts and corporate decisions primarily focus on publicly traded stock companies, I contribute to the literature by extending the analyses to also include private firms and different other organizational forms. In addition, in contrast to concentrating on one risk-taking proxy in most extant insurance studies, I employ various risk measures from different aspects of insurers' operation. Finally, while previous research on insurer risk-taking focuses on the influences of managerial abilities, corporate governance, and insurer characteristics, I significantly extend the literature by demonstrating that local culture has a noteworthy impact on insurer behaviors.

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Table 1: Sample Selection

Sample Screenings (2004-2010)	Observations
All U.S. single unaffiliated insurers (firm-year)	1860
Remove insurers that do not predominantly write annuity or life business (firm-year)	-886
Remove insurers that primarily operate as reinsurers (firm-year)	-211
Remove insurers with missing or non-positive total assets (firm-year)	0
Remove insurers with missing or non-positive surplus (firm-year)	-1
Remove insurers with missing or non-positive net premiums written (firm-year)	-38
Remove insurers with negative reinsurance business fraction (firm-year)	-19
Final sample	705

Table 2: Summary Statistics

	N	Mean	St. Dev.	Percentile 5th	25th	Median	75th	95th
Religiosity Ratios								
Catholic-to-Protestant Ratio	705	1.393	1.498	0.049	0.326	0.893	2.018	4.655
Catholic Ratio	705	0.223	0.141	0.030	0.093	0.194	0.342	0.464
Protestant Ratio	705	0.281	0.164	0.085	0.161	0.220	0.398	0.589
Risk-taking Measures								
Asset Risk	705	0.072	0.110	0.000	0.007	0.029	0.076	0.335
Investment Risk (Std. Dev. ROI)	527	0.007	0.007	0.001	0.003	0.005	0.009	0.022
Total Risk (Std. Dev. ROA)	527	0.013	0.041	0.002	0.003	0.006	0.012	0.039
Firm Characteristics								
Firm Size	705	18.445	2.379	14.672	16.487	18.679	20.195	22.393
Capital-to-Assets Ratio	705	0.245	0.250	0.042	0.077	0.137	0.303	0.888
Net Premium Growth	610	0.265	4.239	-0.348	-0.113	-0.018	0.073	0.649
Reinsurance Use	705	0.164	0.240	0.000	0.004	0.047	0.242	0.747
Geographic HHI	704	0.463	0.376	0.048	0.106	0.312	0.954	1.000
Indicator: Mutual	705	0.112	0.316	0.000	0.000	0.000	0.000	1.000
Indicator: Stock	705	0.705	0.456	0.000	0.000	1.000	1.000	1.000
Indicator: Annuity Writer	705	0.261	0.439	0.000	0.000	0.000	1.000	1.000
Indicator: Life Writer	705	0.739	0.439	0.000	0.000	1.000	1.000	1.000
Indicator: Publicly Traded	705	0.050	0.217	0.000	0.000	0.000	0.000	0.000
Annuity Bus. Fraction	705	0.278	0.403	0.000	0.000	0.068	0.690	0.984
Ordinary Annuity Bus. Fraction	705	0.257	0.384	0.000	0.000	0.057	0.314	0.973
Group Annuity Bus. Fraction	705	0.020	0.102	0.000	0.000	0.000	0.000	0.042
Life Bus. Fraction	705	0.684	0.396	0.011	0.304	0.832	0.980	1.000
A&H Bus. Fraction	705	0.034	0.092	0.000	0.000	0.000	0.025	0.235
Other Bus. Fraction	705	0.004	0.036	0.000	0.000	0.000	0.001	0.017
Industrial Life Bus. Fraction	705	0.011	0.070	0.000	0.000	0.000	0.000	0.029
Ordinary Life Bus. Fraction	705	0.537	0.403	0.000	0.112	0.697	0.907	1.000
Supplemental Bus. Fraction	705	0.004	0.036	0.000	0.000	0.000	0.001	0.016
Credit Life Bus. Fraction	705	0.062	0.223	0.000	0.000	0.000	0.000	0.681
Group Life Bus. Fraction	705	0.075	0.243	0.000	0.000	0.000	0.025	0.767
Group A&H Bus. Fraction	705	0.013	0.052	0.000	0.000	0.000	0.000	0.127
A&H Credit Bus. Fraction	705	0.009	0.069	0.000	0.000	0.000	0.000	0.074
A&H Other Bus. Fraction	705	0.011	0.035	0.000	0.000	0.000	0.003	0.063
Other Fraction	705	0.000	0.004	0.000	0.000	0.000	0.000	0.000
Group Bus. Fraction	705	0.109	0.262	0.000	0.000	0.000	0.054	0.889
Firm Age	705	67.586	33.652	21.000	45.000	55.000	101.000	124.000

Notes: All monetary values are inflation adjusted and converted to constant 2000 US dollars. *Catholic Ratio* (*Protestant Ratio*) is total number of Catholic (Protestant) adherents of a county divided by the county's total population. *Catholic-to-Protestant Ratio* is measured as the ratio of Catholics to Protestants of a county. *Asset Risk* is captured by the ratio of investments in equity securities and real estate to cash and total investments. *Investment Risk* is defined as the standard deviations of firm's ratio of investment income plus realized capital gains to the total invested net admitted assets (ROI) for the past 4 years. *Total Risk* is measured at the standard deviations of firm's ratio of net income to the total net admitted assets (ROA) for the past 4 years. *Firm Size* is defined as the natural logarithm of total net admitted assets. *Capital-to-Assets Ratio* is calculated as the fraction of total capital and surplus to total net admitted assets. *Net Premium Growth* is measured as the change of NPW from the previous year divided by the previous year's NPW. *Reinsurance Use* is constructed as the percentage of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Geographic HHI* is measured as $\Sigma\ (DB_i / TDB)^2$ where DB_i is the value of total direct premiums and annuity considerations in state *i*, and *TDB* is the insurer's total direct premiums and annuity considerations across the U.S. *Mutual* (*Stock*) is a dummy that takes a value of 1 if the insurer is organized as a mutual (stock) company, and 0 otherwise. *Annuity Writer* is an indicator coded equal to 1 if the insurer has over 2/3 of the NPW in ordinary individual annuity and group annuity, and 0 otherwise. *Life Writer* is an indicator coded equal to 1 if the insurer has over 2/3 of the NPW in industrial life, ordinary life, group life, and credit life, and 0 otherwise. *Publicly Traded* is a dummy that is equal to 1 if the insurer is publicly traded, and 0 otherwise. *Annuity Bus. Fraction* is the proportion of insurer's net premiums written (NPW) in ordinary individual annuity and group annuity. *Ordinary Annuity Bus. Fraction* (*Group Annuity Bus. Fraction*) is calculated as the share of NPW in ordinary individual annuity (group annuity). *Life Bus. Fraction* is the share of insurer's NPW in industrial life, ordinary life, group life, and credit life. *A&H Bus. Fraction* is the proportion of insurer's NPW in group Accident & Health, Accident & Health credit, and Accident & Health other insurance. *Other Bus. Fraction* is the share of insurer's NPW in ordinary supplementary contracts and aggregate of all other lines besides ordinary, group, Accident & Health, industrial life, and credit life. *Industrial Life Bus. Fraction* (*Ordinary Life Bus. Fraction*, *Supplemental Bus. Fraction*, *Credit Life Bus. Fraction*, *Group Life Bus. Fraction*, *Group A&H Bus. Fraction*, *A&H Credit Bus. Fraction*, *A&H Other Bus. Fraction*, *Other Fraction*) is the proportion of insurer's NPW in industrial life insurance (ordinary life insurance, ordinary supplementary contracts, credit life insurance, group life insurance, group Accident & Health, Accident & Health credit insurance, Accident & Health other insurance, and aggregate of all other lines). *Group Bus. Fraction* is the share of insurer's NPW in group life, group annuity, and Accident & Health group insurance. *Firm Age* is the number years since incorporation till 2010. All the *Ratios* and *Fractions* variables are expressed in ratios rather than percentages. The data on local religious beliefs is collected from the American Religion Data Archive. Zip code of the corporate administrative office address are taken from *Best's Insurance Reports, Life-Health Edition*. Insurance financial statement data are from statutory filings of insurance companies obtained from *Best's Annual Statement File, Life-Health Edition*.

Table 3: Mean Firm-level Variables Sorted on Religiosity Ratios

Panel A: Variables Sorted on *Catholic-to-Protestant Ratio*

	Low	Q2	Q3	Q4	High	H - L		*p*-value	*t*-stat.
Asset Risk	0.090	0.073	0.048	0.063	0.087	-0.003		0.846	0.194
Investment Risk (Std. Dev. ROI)	0.008	0.006	0.009	0.007	0.007	-0.001		0.178	1.353
Total Risk (Std. Dev. ROA)	0.022	0.008	0.017	0.007	0.012	-0.011		0.211	1.255
Firm Size	16.920	18.439	19.052	18.983	18.831	1.911	***	0.000	-6.947
Capital-to-Assets Ratio	0.287	0.289	0.236	0.206	0.206	-0.081	***	0.005	2.806
Net Premium Growth	0.033	-0.011	1.163	0.071	0.056	0.023		0.702	-0.383
Reinsurance Use	0.237	0.137	0.192	0.130	0.122	-0.115	***	0.000	3.599
Geographic HHI	0.687	0.432	0.378	0.373	0.447	-0.240	***	0.000	5.720
Indicator: Mutual	0.043	0.113	0.057	0.287	0.058	0.015		0.566	-0.574
Indicator: Stock	0.957	0.766	0.901	0.350	0.554	-0.403	***	0.000	8.889
Indicator: Annuity Writer	0.092	0.163	0.291	0.448	0.309	0.217	***	0.000	-4.702
Indicator: Life Writer	0.908	0.837	0.709	0.552	0.691	-0.217	***	0.000	4.702
Indicator: Publicly Traded	0.099	0.000	0.057	0.049	0.043	-0.056	*	0.069	1.828
Annuity Bus. Fraction	0.101	0.203	0.344	0.425	0.314	0.213	***	0.000	-5.574
Ordinary Annuity Bus. Fraction	0.101	0.201	0.306	0.399	0.279	0.178	***	0.000	-4.892
Group Annuity Bus. Fraction	0.000	0.002	0.038	0.026	0.036	0.035	***	0.004	-2.901
Life Bus. Fraction	0.838	0.752	0.633	0.563	0.637	-0.201	***	0.000	5.473
A&H Bus. Fraction	0.061	0.044	0.013	0.009	0.042	-0.019	*	0.083	1.740
Other Bus. Fraction	0.000	0.002	0.010	0.004	0.006	0.006	***	0.000	-4.542
Industrial Life Bus. Fraction	0.020	0.024	0.001	0.002	0.008	-0.012		0.221	1.228
Ordinary Life Bus. Fraction	0.595	0.569	0.511	0.466	0.545	-0.050		0.286	1.069
Supplemental Bus. Fraction	0.000	0.002	0.010	0.004	0.005	0.005	***	0.000	-4.125
Credit Life Bus. Fraction	0.135	0.050	0.054	0.047	0.021	-0.114	***	0.000	4.354
Group Life Bus. Fraction	0.088	0.109	0.068	0.048	0.063	-0.025		0.320	0.995
Group A&H Bus. Fraction	0.011	0.016	-0.001	0.011	0.029	0.018	***	0.009	-2.623
A&H Credit Bus. Fraction	0.030	0.008	0.007	-0.005	0.007	-0.023	***	0.004	2.920
A&H Other Bus. Fraction	0.019	0.019	0.007	0.004	0.006	-0.013	***	0.009	2.638
Other Fraction	0.000	0.000	0.000	0.000	0.001	0.001	*	0.065	-1.853
Group Bus. Fraction	0.100	0.127	0.105	0.084	0.128	0.028		0.357	-0.922
Firm Age	51.539	63.348	55.128	91.266	76.439	24.900	***	0.000	-6.758
No. of Firms	17.857	18.000	21.714	24.000	19.143				

Table 3 (continued)

Panel B: Variables Sorted on *Catholic Ratio*

	Low	Q2	Q3	Q4	High	H - L		*p*-value	*t*-stat.
Asset Risk	0.107	0.051	0.066	0.052	0.085	-0.023		0.116	1.578
Investment Risk (Std. Dev. ROI)	0.009	0.008	0.007	0.006	0.007	-0.002	*	0.093	1.690
Total Risk (Std. Dev. ROA)	0.021	0.014	0.010	0.010	0.011	-0.010		0.243	1.172
Firm Size	17.354	18.503	18.702	19.159	18.503	1.149	***	0.000	-4.428
Capital-to-Assets Ratio	0.269	0.274	0.283	0.206	0.191	-0.078	***	0.005	2.831
Net Premium Growth	-0.014	0.969	0.003	0.213	0.085	0.099	**	0.023	-2.281
Reinsurance Use	0.200	0.183	0.169	0.158	0.108	-0.092	***	0.002	3.197
Geographic HHI	0.627	0.426	0.411	0.436	0.414	-0.213	***	0.000	4.957
Indicator: Mutual	0.043	0.105	0.094	0.224	0.094	0.051	*	0.091	-1.698
Indicator: Stock	0.957	0.818	0.827	0.448	0.475	-0.483	***	0.000	10.591
Indicator: Annuity Writer	0.071	0.245	0.273	0.364	0.353	0.282	***	0.000	-6.133
Indicator: Life Writer	0.929	0.755	0.727	0.636	0.647	-0.282	***	0.000	6.133
Indicator: Publicly Traded	0.121	0.035	0.050	0.021	0.022	-0.099	***	0.001	3.265
Annuity Bus. Fraction	0.093	0.299	0.280	0.365	0.351	0.257	***	0.000	-6.796
Ordinary Annuity Bus. Fraction	0.093	0.291	0.227	0.329	0.347	0.254	***	0.000	-6.705
Group Annuity Bus. Fraction	0.001	0.008	0.052	0.036	0.004	0.003		0.120	-1.561
Life Bus. Fraction	0.845	0.658	0.697	0.616	0.606	-0.240	***	0.000	6.595
A&H Bus. Fraction	0.061	0.035	0.019	0.014	0.040	-0.022	**	0.042	2.044
Other Bus. Fraction	0.000	0.008	0.004	0.005	0.004	0.004	***	0.001	-3.266
Industrial Life Bus. Fraction	0.020	0.000	0.025	0.001	0.009	-0.011		0.237	1.184
Ordinary Life Bus. Fraction	0.613	0.524	0.511	0.499	0.537	-0.075	*	0.095	1.673
Supplemental Bus. Fraction	0.000	0.008	0.004	0.005	0.003	0.003	***	0.004	-2.895
Credit Life Bus. Fraction	0.122	0.044	0.107	0.015	0.021	-0.101	***	0.000	3.952
Group Life Bus. Fraction	0.091	0.090	0.053	0.102	0.039	-0.052	**	0.025	2.254
Group A&H Bus. Fraction	0.017	0.005	0.006	0.011	0.027	0.010		0.155	-1.427
A&H Credit Bus. Fraction	0.024	0.020	0.003	-0.008	0.007	-0.017	**	0.019	2.351
A&H Other Bus. Fraction	0.020	0.010	0.011	0.010	0.005	-0.015	***	0.003	3.015
Other Fraction	0.000	0.000	0.000	0.000	0.001	0.001		0.137	-1.490
Group Bus. Fraction	0.108	0.103	0.111	0.150	0.070	-0.038		0.138	1.486
Firm Age	56.085	58.748	59.698	79.448	84.029	27.944	***	0.000	-7.661
No. of Firms	17.000	21.429	19.714	21.286	21.286				

Table 3 (continued)

Panel C: Variables Sorted on *Protestant Ratio*

	Low	Q2	Q3	Q4	High	H - L		*p*-value	*t*-stat.
Asset Risk	0.093	0.053	0.048	0.079	0.088	-0.005		0.740	0.333
Investment Risk (Std. Dev. ROI)	0.008	0.007	0.007	0.007	0.008	0.000		0.958	-0.053
Total Risk (Std. Dev. ROA)	0.012	0.011	0.010	0.010	0.021	0.009		0.299	-1.042
Firm Size	18.748	19.046	19.569	17.777	17.087	-1.662	***	0.000	5.776
Capital-to-Assets Ratio	0.271	0.152	0.181	0.337	0.284	0.013		0.669	-0.428
Net Premium Growth	0.045	0.980	0.239	-0.051	0.046	0.000		0.997	-0.003
Reinsurance Use	0.127	0.152	0.152	0.146	0.240	0.113	***	0.000	-3.613
Geographic HHI	0.449	0.354	0.333	0.502	0.678	0.229	***	0.000	-5.295
Indicator: Mutual	0.071	0.199	0.149	0.128	0.014	-0.057	**	0.018	2.375
Indicator: Stock	0.674	0.468	0.560	0.837	0.986	0.312	***	0.000	-7.636
Indicator: Annuity Writer	0.270	0.433	0.376	0.135	0.092	-0.177	***	0.000	3.961
Indicator: Life Writer	0.730	0.567	0.624	0.865	0.908	0.177	***	0.000	-3.961
Indicator: Publicly Traded	0.092	0.007	0.050	0.000	0.099	0.007		0.840	-0.202
Annuity Bus. Fraction	0.283	0.473	0.363	0.160	0.110	-0.173	***	0.000	4.714
Ordinary Annuity Bus. Fraction	0.237	0.450	0.331	0.159	0.109	-0.128	***	0.000	3.787
Group Annuity Bus. Fraction	0.046	0.023	0.032	0.001	0.000	-0.046	***	0.001	3.247
Life Bus. Fraction	0.680	0.500	0.621	0.798	0.823	0.143	***	0.000	-3.899
A&H Bus. Fraction	0.032	0.015	0.013	0.041	0.067	0.035	***	0.010	-2.602
Other Bus. Fraction	0.005	0.013	0.003	0.001	0.000	-0.004	***	0.000	4.039
Industrial Life Bus. Fraction	0.007	0.002	0.001	0.023	0.021	0.014		0.146	-1.458
Ordinary Life Bus. Fraction	0.542	0.459	0.509	0.587	0.587	0.045		0.325	-0.985
Supplemental Bus. Fraction	0.003	0.013	0.003	0.001	0.000	-0.003	***	0.000	3.714
Credit Life Bus. Fraction	0.069	0.023	0.010	0.073	0.133	0.064	*	0.051	-1.958
Group Life Bus. Fraction	0.062	0.015	0.101	0.115	0.082	0.020		0.428	-0.793
Group A&H Bus. Fraction	0.024	0.004	0.011	0.017	0.010	-0.014	**	0.020	2.344
A&H Credit Bus. Fraction	0.002	0.006	-0.003	0.011	0.031	0.029	***	0.010	-2.594
A&H Other Bus. Fraction	0.007	0.005	0.005	0.013	0.026	0.019	***	0.001	-3.328
Other Fraction	0.001	0.000	0.000	0.000	0.000	-0.001	*	0.067	1.840
Group Bus. Fraction	0.132	0.041	0.144	0.134	0.092	-0.040		0.188	1.321
Firm Age	68.582	86.050	77.418	57.475	48.404	-20.177	***	0.000	5.618
No. of Firms	20.143	23.286	22.571	17.857	16.857				

Notes: I sort firm characteristics (all the variables except for *No. of Firms*) into quintiles based on the local religiosity ratios, and then calculate the means for each quintile. I also report the differences between the top and bottom quintiles, and the associated *p*-value and *t*-statistics. With regard to *No. of Firms*, for each year during 2004-2010, I sort the headquarter counties of sample insurers into quintiles based on their religiosity ratios, then count the number of insurers in each quintile, and report the time-series means. Panel A, Panel B, and Panel C reports mean firm-level variables sorted on Catholic-to-Protestant ratio, Catholic ratio, and Protestant ratio, respectively. All monetary values are inflation adjusted and converted to constant 2000 US dollars. *Catholic Ratio* (*Protestant Ratio*) is total number of Catholic (Protestant) adherents of a county divided by the county's total population. *Catholic-to-Protestant Ratio* is measured as the ratio of Catholics to Protestants of a county. *Asset Risk* is captured by the ratio of investments in equity securities and real estate to cash and total investments. *Investment Risk* is defined as the standard deviations of firm's ratio of investment income plus realized capital gains to the total invested net admitted assets (ROI) for the past 4 years. *Total Risk* is measured at the standard deviations of firm's ratio of net income to the total net admitted assets (ROA) for the past 4 years. *Firm Size* is defined as the natural logarithm of total net admitted assets. *Capital-to-Assets Ratio* is calculated as the fraction of total capital and surplus to total net admitted assets. *Net Premium Growth* is measured as the change of NPW from the previous year divided by the previous year's NPW. *Reinsurance Use* is constructed as the percentage of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Geographic HHI* is measured as $\Sigma\ (DB_i / TDB)^2$ where DB_i is the value of total direct premiums and annuity considerations in state *i*, and *TDB* is the insurer's total direct premiums and annuity considerations across the U.S. *Mutual* (*Stock*) is a dummy that takes a value of 1 if the insurer is organized as a mutual (stock) company, and 0 otherwise. *Annuity Writer* is an indicator coded equal to 1 if the insurer has over 2/3 of the NPW in ordinary individual annuity and group annuity, and 0 otherwise. *Life Writer* is an indicator coded equal to 1 if the insurer has over 2/3 of the NPW in industrial life, ordinary life, group life, and credit life, and 0 otherwise. *Publicly Traded* is a dummy that is equal to 1 if the insurer is publicly traded, and 0 otherwise. *Annuity Bus. Fraction* is the proportion of insurer's net premiums written (NPW) in ordinary individual annuity and group annuity. *Ordinary Annuity Bus. Fraction* (*Group Annuity Bus. Fraction*) is calculated as the share of NPW in ordinary individual annuity (group annuity). *Life Bus. Fraction* is the share of insurer's NPW in industrial life, ordinary life, group life, and credit life. *A&H Bus. Fraction* is the proportion of insurer's NPW in group Accident & Health, Accident & Health credit, and Accident & Health other insurance. *Other Bus. Fraction* is the share of insurer's NPW in ordinary supplementary contracts and aggregate of all other lines besides ordinary, group, Accident & Health, industrial life, and credit life. *Industrial Life Bus. Fraction* (*Ordinary Life Bus. Fraction*, *Supplemental Bus. Fraction*, *Credit Life Bus. Fraction*, *Group Life Bus. Fraction*, *Group A&H Bus. Fraction*, *A&H Credit Bus. Fraction*, *A&H Other Bus. Fraction*, *Other Fraction*) is the proportion of insurer's NPW in industrial life insurance (ordinary life insurance, ordinary supplementary contracts, credit life insurance, group life insurance, group Accident & Health, Accident & Health credit insurance, Accident & Health other insurance, and aggregate of all other lines). *Group Bus. Fraction* is the share of insurer's NPW in group life, group annuity, and Accident & Health group insurance. *Firm Age* is the number years since incorporation till 2010. All the *Ratios* and *Fractions* variables are expressed in ratios rather than percentages. The data on local religious beliefs is collected from the American Religion Data Archive. Zip code of the corporate administrative office address are taken from *Best's Insurance Reports, Life-Health Edition*. Insurance financial statement data are from statutory filings of insurance companies obtained from *Best's Annual Statement File, Life-Health Edition*. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4: Multi-period Logit Regression on Annuity Writer Indicator

	Indicator: Annuity Writer		
Catholic-to-Protestant Ratio	0.071		
	(0.119)		
Catholic Ratio		2.170*	
		(1.317)	
Protestant Ratio			-3.538**
			(1.464)
Dem.: Age	0.200**	0.177**	0.194**
	(0.081)	(0.082)	(0.077)
Dem.: Education	0.064	0.059	0.052
	(0.049)	(0.049)	(0.049)
Dem.: Income	-0.151*	-0.154*	-0.157*
	(0.091)	(0.089)	(0.089)
Dem.: Population	0.266*	0.210	0.148
	(0.159)	(0.160)	(0.159)
Dem.: MaletoFemale	0.034	0.044	0.036
	(0.064)	(0.060)	(0.058)
Dem.: Minority	-0.027	-0.021	-0.017
	(0.019)	(0.021)	(0.020)
Dem.: Married	-0.007	-0.010	-0.010
	(0.020)	(0.021)	(0.021)
Dem.: Population Density	0.057**	0.060**	0.055**
	(0.025)	(0.026)	(0.026)
Constant	-10.451	-10.591	-8.595
	(7.166)	(6.808)	(6.732)
Year Dummies	Yes	Yes	Yes
Observations	705	705	705
Pseudo R-square	0.081	0.089	0.108

Notes: This table presents the results from a multi-period Logit regression on annuity writer indicator with year fixed-effects. All monetary values are inflation adjusted and converted to constant 2000 US dollars. *Catholic Ratio* (*Protestant Ratio*) is total number of Catholic (Protestant) adherents of a county divided by the county's total population. *Catholic-to-Protestant Ratio* is measured as the ratio of Catholics to Protestants of a county. *Annuity Writer* is an indicator coded equal to 1 if the insurer has over 2/3 of the net premiums written in ordinary individual annuity and group annuity, and 0 otherwise. The county demographic variables include median age of the county population (*Age*), the fraction of highly educated people (bachelor's degree or higher) among the population 25 years or older (*Education*), the per capita personal income (*Income*), the county's total population (*Population*), the fraction of the minority population that is not White alone, non-Hispanic (*Minority*), the ratio of married households to the total number of households (*Married*), the ratio of the male population to the female population (*MaletoFemale*), and the total population of a county divided by the county's size of area (*Population Density*). All the *Ratios* variables are expressed in ratios rather than percentages. The data on local religious beliefs is collected from the American Religion Data Archive. Zip code of the corporate administrative office address are taken from *Best's Insurance Reports, Life-Health Edition*. I obtain the county-level demographic data from the U.S. Census Bureau. I calculate the *t*-statistics using two-way robust standard errors (in parentheses) corrected for clustering by firm and by year. The reported significance levels are based on *t*-statistics. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5: Panel Tobit Regression of Asset Risk on Religiosity Ratios

	Asset Risk								
	All Insurers			Annuity Insurers			Life Insurers		
Catholic-to-Protestant Ratio	0.495			1.273**			0.663		
	(0.618)			(0.510)			(0.752)		
Catholic Ratio		2.488			14.319**			8.536	
		(7.037)			(5.935)			(8.429)	
Protestant Ratio			-8.224			-9.795**			-10.251
			(9.289)			(4.482)			(10.634)
Firm Size	-0.495	-0.457	-0.550	-0.584**	-0.454	-0.685**	-0.411	-0.398	-0.430
	(0.568)	(0.558)	(0.582)	(0.285)	(0.313)	(0.276)	(0.717)	(0.711)	(0.714)
Capital-to-Assets Ratio	-4.088	-4.039	-4.701	0.001	1.148	-0.709	-7.752	-7.830	-8.301
	(6.025)	(6.010)	(5.879)	(4.028)	(4.143)	(3.822)	(6.624)	(6.575)	(6.529)
Net Premium Growth	-0.062	-0.061	-0.069	-0.196***	-0.189***	-0.222***	2.179***	2.138***	2.165***
	(0.145)	(0.145)	(0.143)	(0.028)	(0.029)	(0.032)	(0.481)	(0.484)	(0.450)
Reinsurance Use	-2.558	-2.647	-2.421	-6.373**	-6.415**	-6.346**	1.485	1.532	1.744
	(5.644)	(5.662)	(5.671)	(2.800)	(2.869)	(3.111)	(5.929)	(5.960)	(5.954)
Geographic HHI	1.244	1.343	1.752	-5.214***	-5.822***	-4.700***	5.570	5.630	6.347
	(3.479)	(3.472)	(3.305)	(1.505)	(1.539)	(1.459)	(4.172)	(4.155)	(4.084)
Indicator: Mutual	-5.013*	-5.324**	-4.864*	3.766**	3.616**	3.580**	-10.415***	-10.613***	-10.339***
	(2.638)	(2.607)	(2.584)	(1.444)	(1.577)	(1.463)	(3.828)	(3.746)	(3.764)
Indicator: Stock	-4.671*	-4.859**	-4.228*	1.418	2.266**	1.328	-10.008***	-9.794***	-9.460**
	(2.389)	(2.453)	(2.405)	(1.014)	(1.057)	(1.163)	(3.761)	(3.763)	(3.835)
Indicator: Annuity Writer	-5.216***	-5.395***	-5.473***						
	(1.986)	(1.979)	(1.958)						
Indicator: Publicly Traded	13.394*	13.691*	13.787**	1.759	2.310	2.947*	18.097*	19.043*	18.534*
	(7.075)	(7.192)	(6.838)	(2.102)	(1.785)	(1.673)	(10.594)	(10.872)	(10.109)
Dem.: Age	-0.750	-0.777*	-0.750	-0.126	-0.221	-0.221	-1.242*	-1.328*	-1.224*
	(0.470)	(0.468)	(0.462)	(0.210)	(0.214)	(0.217)	(0.713)	(0.735)	(0.692)
Dem.: Education	-0.238	-0.253	-0.271	-0.126	-0.249	-0.182	-0.278	-0.301	-0.327
	(0.222)	(0.220)	(0.228)	(0.247)	(0.250)	(0.236)	(0.263)	(0.266)	(0.276)
Dem.: Income	-0.039	0.014	-0.018	-0.314	-0.144	-0.114	0.184	0.216	0.209
	(0.346)	(0.340)	(0.332)	(0.466)	(0.486)	(0.428)	(0.416)	(0.421)	(0.420)
Dem.: Population	1.400*	1.495*	1.222	3.150***	3.171***	3.257***	0.391	0.353	0.121
	(0.834)	(0.824)	(0.889)	(0.335)	(0.330)	(0.297)	(0.966)	(0.911)	(1.056)
Dem.: MaletoFemale	-0.656*	-0.685*	-0.709**	-0.110	-0.077	-0.265*	-0.611	-0.643	-0.681
	(0.372)	(0.366)	(0.354)	(0.157)	(0.165)	(0.149)	(0.480)	(0.461)	(0.454)
Dem.: Minority	-0.012	-0.019	-0.004	0.021	0.031	0.016	-0.021	-0.009	-0.014
	(0.081)	(0.083)	(0.089)	(0.095)	(0.105)	(0.099)	(0.100)	(0.101)	(0.108)
Dem.: Married	0.028	0.039	0.031	0.128***	0.129***	0.144***	0.008	0.002	0.013
	(0.094)	(0.093)	(0.093)	(0.046)	(0.047)	(0.050)	(0.124)	(0.120)	(0.119)
Dem.: Population Density	0.078	0.074	0.071	0.114	0.122	0.063	-0.185*	-0.187*	-0.198*
	(0.100)	(0.103)	(0.101)	(0.079)	(0.090)	(0.073)	(0.110)	(0.110)	(0.111)
Constant	116.431**	118.845***	125.815***	35.880*	31.614	57.285***	129.396**	134.359**	140.198**
	(46.265)	(45.678)	(46.329)	(19.467)	(21.309)	(18.714)	(55.676)	(54.952)	(56.120)
Sigma	9.936***	9.949***	9.900***	2.609***	2.631***	2.609***	10.909***	10.896***	10.848***
	(1.045)	(1.055)	(1.015)	(0.248)	(0.256)	(0.231)	(1.105)	(1.117)	(1.071)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	610	610	610	168	168	168	442	442	442
Pseudo R-square	0.038	0.038	0.039	0.263	0.261	0.263	0.046	0.046	0.047

Notes: All monetary values are inflation adjusted and converted to constant 2000 US dollars. *Asset Risk* is captured by the ratio of investments in equity securities and real estate to cash and total investments. *Catholic Ratio* (*Protestant Ratio*) is total number of Catholic (Protestant) adherents of a county divided by the county's total population. *Catholic-to-Protestant Ratio* is measured as the ratio of Catholics to Protestants of a county. *Firm Size* is defined as the natural logarithm of total net admitted assets. *Capital-to-Assets Ratio* is calculated as the fraction of total capital and surplus to total net admitted assets. *Net Premium Growth* is measured as the change of NPW from the previous year divided by the previous year's NPW. *Reinsurance Use* is constructed as the percentage of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Geographic HHI* is measured as $\Sigma\ (DB_i\ /TDB)^2$ where DB_i is the value of total direct premiums and annuity considerations in state *i*, and *TDB* is the insurer's total direct premiums and annuity considerations across the U.S. *Mutual* (*Stock*) is a dummy that takes a value of 1 if the insurer is organized as a mutual (stock) company, and 0 otherwise. *Life Writer* is an indicator coded equal to 1 if the insurer has over 2/3 of the NPW in industrial life, ordinary life, group life, and credit life, and 0 otherwise. *Publicly Traded* is a dummy that is equal to 1 if the insurer is publicly traded, and 0 otherwise. The county demographic variables include median age of the county population (*Age*), the fraction of highly educated people (bachelor's degree or higher) among the population 25 years or older (*Education*), the per capita personal income (*Income*), the county's total population (*Population*), the ratio of the male population to the female population (*MaletoFemale*), the fraction of the minority population that is not White alone, non-Hispanic (*Minority*), the ratio of married households to the total number of households (*Married*), and the total population of a county divided by the county's size of area (*Population Density*). All the *Ratios* and *Fractions* variables are expressed in ratios rather than percentages. The data on local religious beliefs is collected from the American Religion Data Archive. Zip code of the corporate administrative office address are taken from *Best's Insurance Reports, Life-Health Edition*. Insurance financial statement data are from statutory filings of insurance companies obtained from *Best's Annual Statement File, Life-Health Edition*. I obtain the county-level demographic data from the U.S. Census Bureau. I include year fixed effects in each regression. To improve readability of the coefficient of the explanatory variables, the dependent variables have been multiplied by 100 in all models. The standard errors (in parentheses) are corrected by firm-level clustering in all models. The reported significance levels are based on *t*-statistics. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Panel OLS Regression of Investment Risk on Religiosity Ratios

	Investment Risk								
	All Insurers			Annuity Insurers			Life Insurers		
Catholic-to-Protestant Ratio	-0.002			0.309*			-0.034		
	(0.047)			(0.173)			(0.038)		
Catholic Ratio		-0.372			1.671			-0.550	
		(0.374)			(1.075)			(0.459)	
Protestant Ratio			-0.177			-2.378***			0.327
			(0.540)			(0.813)			(0.480)
Firm Size	-0.016	-0.014	-0.019	0.094	0.112	0.054	-0.046	-0.046	-0.047
	(0.027)	(0.028)	(0.027)	(0.057)	(0.069)	(0.038)	(0.029)	(0.029)	(0.029)
Capital-to-Assets Ratio	0.521	0.538	0.502	1.896*	2.058*	1.838*	0.417	0.430	0.423
	(0.418)	(0.425)	(0.418)	(1.079)	(1.188)	(1.009)	(0.370)	(0.369)	(0.371)
Net Premium Growth	0.011***	0.011***	0.011***	0.004	0.003	-0.000	0.162***	0.165***	0.164***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.014)	(0.015)	(0.015)
Reinsurance Use	0.155	0.144	0.154	1.220*	1.271	0.864	0.235	0.227	0.244
	(0.269)	(0.264)	(0.269)	(0.730)	(0.850)	(0.658)	(0.229)	(0.222)	(0.226)
Geographic HHI	0.016	0.025	0.022	0.129	0.099	0.288	-0.126	-0.132	-0.157
	(0.150)	(0.147)	(0.154)	(0.358)	(0.443)	(0.315)	(0.157)	(0.155)	(0.166)
Indicator: Mutual	0.162	0.152	0.173	0.384	0.279	0.428	-0.208	-0.199	-0.190
	(0.167)	(0.166)	(0.166)	(0.347)	(0.379)	(0.371)	(0.185)	(0.174)	(0.178)
Indicator: Stock	0.292*	0.259*	0.314*	0.717***	0.720***	0.742***	-0.095	-0.122	-0.099
	(0.158)	(0.155)	(0.175)	(0.204)	(0.233)	(0.224)	(0.101)	(0.106)	(0.110)
Indicator: Annuity Writer	0.164	0.165	0.165						
	(0.116)	(0.107)	(0.109)						
Indicator: Publicly Traded	-0.003	-0.026	0.001	-0.756	-0.586	-0.594	0.145	0.080	0.139
	(0.168)	(0.155)	(0.166)	(0.572)	(0.466)	(0.392)	(0.168)	(0.167)	(0.161)
Dem.: Age	0.015	0.021	0.015	0.032	0.014	0.022	0.022	0.029	0.022
	(0.026)	(0.025)	(0.026)	(0.037)	(0.040)	(0.028)	(0.025)	(0.026)	(0.025)
Dem.: Education	0.017	0.019	0.016	-0.004	-0.023	-0.009	0.028*	0.030*	0.030*
	(0.012)	(0.012)	(0.012)	(0.037)	(0.029)	(0.033)	(0.015)	(0.015)	(0.016)
Dem.: Income	-0.028*	-0.028	-0.029*	-0.025	0.020	0.001	-0.033*	-0.034*	-0.035**
	(0.016)	(0.018)	(0.017)	(0.071)	(0.044)	(0.057)	(0.018)	(0.019)	(0.018)
Dem.: Population	0.099	0.115	0.089	0.155	0.211*	0.171*	-0.007	-0.000	0.003
	(0.095)	(0.093)	(0.095)	(0.109)	(0.110)	(0.092)	(0.058)	(0.053)	(0.072)
Dem.: MaletoFemale	0.015	0.014	0.014	0.053	0.043	0.029	0.015	0.017	0.018
	(0.020)	(0.018)	(0.017)	(0.050)	(0.040)	(0.031)	(0.019)	(0.018)	(0.017)
Dem.: Minority	0.007	0.006	0.007	-0.019	-0.021	-0.014	0.007	0.006	0.008*
	(0.004)	(0.004)	(0.005)	(0.020)	(0.020)	(0.018)	(0.005)	(0.004)	(0.004)
Dem.: Married	0.002	0.003	0.002	-0.002	-0.001	0.001	0.003	0.003	0.002
	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)
Dem.: Population Density	0.005	0.004	0.005	0.008	0.004	-0.000	0.001	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.015)	(0.011)	(0.011)	(0.005)	(0.005)	(0.005)
Constant	-1.174	-1.316	-0.946	-7.655	-6.909	-3.765	-0.584	-0.974	-1.016
	(1.718)	(1.625)	(1.628)	(6.401)	(5.786)	(3.464)	(1.681)	(1.647)	(1.602)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	527	527	527	154	154	154	373	373	373
Adj. R-square	0.173	0.175	0.174	0.404	0.363	0.420	0.233	0.235	0.233

Notes: All monetary values are inflation adjusted and converted to constant 2000 US dollars. *Investment Risk* is defined as the standard deviations of firm's ratio of investment income plus realized capital gains to the total invested net admitted assets (ROI) for the past 4 years. *Catholic Ratio* (*Protestant Ratio*) is total number of Catholic (Protestant) adherents of a county divided by the county's total population. *Catholic-to-Protestant Ratio* is measured as the ratio of Catholics to Protestants of a county. *Firm Size* is defined as the natural logarithm of total net admitted assets. *Capital-to-Assets Ratio* is calculated as the fraction of total capital and surplus to total net admitted assets. *Net Premium Growth* is measured as the change of NPW from the previous year divided by the previous year's NPW. *Reinsurance Use* is constructed as the percentage of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Geographic HHI* is measured as $\Sigma\ (DB_i\ /TDB)^2$ where DB_i is the value of total direct premiums and annuity considerations in state i, and *TDB* is the insurer's total direct premiums and annuity considerations across the U.S. *Mutual* (*Stock*) is a dummy that takes a value of 1 if the insurer is organized as a mutual (stock) company, and 0 otherwise. *Annuity Writer* is an indicator coded equal to 1 if the insurer has over 2/3 of the NPW in ordinary individual annuity and group annuity, and 0 otherwise. *Publicly Traded* is a dummy that is equal to 1 if the insurer is publicly traded, and 0 otherwise. The county demographic variables include median age of the county population (*Age*), the fraction of highly educated people (bachelor's degree or higher) among the population 25 years or older (*Education*), the per capita personal income (*Income*), the county's total population (*Population*), the ratio of the male population to the female population (*MaletoFemale*), the fraction of the minority population that is not White alone, non-Hispanic (*Minority*), the ratio of married households to the total number of households (*Married*), and the total population of a county divided by the county's size of area (*Population Density*). All the *Ratios* and *Fractions* variables are expressed in ratios rather than percentages. The data on local religious beliefs is collected from the American Religion Data Archive. Zip code of the corporate administrative office address are taken from *Best's Insurance Reports, Life-Health Edition*. Insurance financial statement data are from statutory filings of insurance companies obtained from *Best's Annual Statement File, Life-Health Edition*. I obtain the county-level demographic data from the U.S. Census Bureau. I include year fixed effects in each regression. To improve readability of the coefficient of the explanatory variables, the dependent variable has been multiplied by 100 in all models. The *t*-statistics are calculated using two-way clustered standard errors (in parentheses) by firm and by year in all models. The reported significance levels are based on *t*-statistics. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 7: Panel OLS Regression of Total Risk on Religiosity Ratios

	Total Risk								
	All Insurers			Annuity Insurers			Life Insurers		
Catholic-to-Protestant Ratio	0.098			0.305*			0.061		
	(0.174)			(0.167)			(0.188)		
Catholic Ratio		-1.363			1.648*			-2.265	
		(1.895)			(0.987)			(2.468)	
Protestant Ratio			2.143			-2.292***			3.289
			(3.250)			(0.820)			(4.058)
Firm Size	-0.263**	-0.244**	-0.217**	0.042	0.059	0.003	-0.373**	-0.352**	-0.337**
	(0.124)	(0.118)	(0.108)	(0.059)	(0.074)	(0.040)	(0.159)	(0.149)	(0.142)
Capital-to-Assets Ratio	4.984**	5.088**	5.245**	1.966**	2.126**	1.912**	5.517***	5.671***	5.786**
	(2.010)	(2.094)	(2.203)	(0.832)	(0.899)	(0.763)	(2.097)	(2.179)	(2.310)
Net Premium Growth	0.134***	0.133***	0.136***	0.130***	0.129***	0.125***	0.267**	0.277**	0.287**
	(0.010)	(0.010)	(0.012)	(0.004)	(0.005)	(0.003)	(0.122)	(0.131)	(0.139)
Reinsurance Use	1.812	1.742	1.809	0.325	0.376	-0.015	1.682	1.563	1.598
	(1.874)	(1.869)	(1.922)	(0.631)	(0.787)	(0.659)	(1.754)	(1.749)	(1.752)
Geographic HHI	-1.623	-1.554	-1.676	-0.069	-0.099	0.086	-2.609*	-2.592*	-2.843*
	(1.087)	(1.054)	(1.133)	(0.372)	(0.447)	(0.329)	(1.523)	(1.486)	(1.660)
Indicator: Mutual	0.853	0.746	0.666	0.143	0.039	0.181	0.766	0.612	0.564
	(0.605)	(0.562)	(0.541)	(0.295)	(0.379)	(0.316)	(0.821)	(0.768)	(0.735)
Indicator: Stock	0.607	0.404	0.279	0.773***	0.776***	0.793***	0.640	0.312	0.162
	(0.516)	(0.506)	(0.633)	(0.205)	(0.256)	(0.222)	(0.761)	(0.720)	(0.790)
Indicator: Annuity Writer	0.721	0.684	0.675						
	(0.454)	(0.419)	(0.427)						
Indicator: Publicly Traded	-0.608	-0.675	-0.631	-0.761	-0.593	-0.598	-0.519	-0.811	-0.628
	(0.512)	(0.428)	(0.453)	(0.567)	(0.458)	(0.379)	(0.585)	(0.576)	(0.694)
Dem.: Age	0.214	0.237	0.225	0.004	-0.014	-0.006	0.372	0.418	0.402
	(0.140)	(0.151)	(0.145)	(0.038)	(0.040)	(0.028)	(0.233)	(0.254)	(0.248)
Dem.: Education	0.149**	0.157**	0.160**	-0.038	-0.057**	-0.043	0.230**	0.240**	0.255**
	(0.059)	(0.065)	(0.073)	(0.035)	(0.028)	(0.032)	(0.090)	(0.096)	(0.114)
Dem.: Income	-0.296**	-0.283**	-0.278**	0.024	0.069	0.051	-0.421**	-0.411*	-0.413**
	(0.140)	(0.143)	(0.134)	(0.068)	(0.046)	(0.056)	(0.207)	(0.209)	(0.204)
Dem.: Population	0.068	0.173	0.232	0.163	0.219*	0.181*	0.018	0.152	0.332
	(0.167)	(0.163)	(0.236)	(0.117)	(0.117)	(0.099)	(0.268)	(0.272)	(0.502)
Dem.: MaletoFemale	0.068	0.058	0.069	0.042	0.032	0.018	0.017	0.012	0.025
	(0.079)	(0.075)	(0.076)	(0.044)	(0.036)	(0.027)	(0.092)	(0.088)	(0.085)
Dem.: Minority	0.049	0.043	0.043	-0.014	-0.016	-0.009	0.055	0.046	0.049
	(0.067)	(0.066)	(0.063)	(0.016)	(0.016)	(0.016)	(0.071)	(0.070)	(0.066)
Dem.: Married	0.008	0.015	0.014	-0.006	-0.004	-0.002	0.004	0.016	0.014
	(0.017)	(0.018)	(0.020)	(0.007)	(0.006)	(0.007)	(0.024)	(0.024)	(0.025)
Dem.: Population Density	0.037	0.032	0.034	-0.000	-0.004	-0.008	0.029	0.029	0.032
	(0.026)	(0.025)	(0.025)	(0.014)	(0.012)	(0.011)	(0.033)	(0.033)	(0.036)
Constant	-7.984	-8.410	-10.669	-4.413	-3.670	-0.599	-6.476	-8.069	-10.801
	(9.930)	(9.634)	(11.196)	(6.181)	(5.705)	(3.326)	(11.892)	(11.927)	(13.805)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	527	527	527	154	154	154	373	373	373
Adj. R-square	0.149	0.149	0.152	0.833	0.819	0.837	0.135	0.137	0.142

Notes: All monetary values are inflation adjusted and converted to constant 2000 US dollars. *Total Risk* is measured at the standard deviations of firm's ratio of net income to the total net admitted assets (ROA) for the past 4 years. *Catholic Ratio* (*Protestant Ratio*) is total number of Catholic (Protestant) adherents of a county divided by the county's total population. *Catholic-to-Protestant Ratio* is measured as the ratio of Catholics to Protestants of a county. *Firm Size* is defined as the natural logarithm of total net admitted assets. *Capital-to-Assets Ratio* is calculated as the fraction of total capital and surplus to total net admitted assets. *Net Premium Growth* is measured as the change of NPW from the previous year divided by the previous year's NPW. *Reinsurance Use* is constructed as the percentage of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Geographic HHI* is measured as $\Sigma\ (DB_i\ /TDB)^2$ where DB_i is the value of total direct premiums and annuity considerations in state *i*, and *TDB* is the insurer's total direct premiums and annuity considerations across the U.S. *Mutual* (*Stock*) is a dummy that takes a value of 1 if the insurer is organized as a mutual (stock) company, and 0 otherwise. *Annuity Writer* is an indicator coded equal to 1 if the insurer has over 2/3 of the NPW in ordinary individual annuity and group annuity, and 0 otherwise. *Publicly Traded* is a dummy that is equal to 1 if the insurer is publicly traded, and 0 otherwise. The county demographic variables include median age of the county population (*Age*), the fraction of highly educated people (bachelor's degree or higher) among the population 25 years or older (*Education*), the per capita personal income (*Income*), the county's total population (*Population*), the ratio of the male population to the female population (*MaletoFemale*), the fraction of the minority population that is not White alone, non-Hispanic (*Minority*), the ratio of married households to the total number of households (*Married*), and the total population of a county divided by the county's size of area (*Population Density*). All the *Ratios* and *Fractions* variables are expressed in ratios rather than percentages. The data on local religious beliefs is collected from the American Religion Data Archive. Zip code of the corporate administrative office address are taken from *Best's Insurance Reports, Life-Health Edition*. Insurance financial statement data are from statutory filings of insurance companies obtained from *Best's Annual Statement File, Life-Health Edition*. I obtain the county-level demographic data from the U.S. Census Bureau. I include year fixed effects in each regression. To improve readability of the coefficient of the explanatory variables, the dependent variable has been multiplied by 100 in all models. The *t*-statistics are calculated using two-way clustered standard errors (in parentheses) by firm and by year in all models. The reported significance levels are based on *t*-statistics. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.