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Three Essays On Insurance Asset Management

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ABSTRACT

The insurance industry manages a large amount of financial assets. In recent years, a growing number of investment companies are providing insurance asset management solutions, and the use of external asset management by the insurance industry is increasing over time. Therefore, understanding insurance asset management is important for academics and practitioners in both insurance and general finance.

In the first essay, we investigate industrial portfolio tilt (referred to as "industry bias") in the U.S. property liability insurers' common stock portfolios. We find that U.S. property-liability insurers exhibit a negative industry bias by tilting their portfolios away from their own industry. We examine the nature of the industry bias and find that property-liability insurers have asymmetric information in investing in industrially close stocks but that their underwriting risk drives their portfolio tilt away from these stocks. Therefore, the property-liability insurers' negative industry bias is driven by hedging in spite of information advantages.

In the second essay, we investigate the betting-against-beta strategy in the presence of leverage in the U.S. property-liability insurance industry and empirically test whether these institutional investors' leverage is an important determinant of their portfolio beta choice. Through empirical analysis, we find that property-liability insurers' portfolio beta is not negatively related to their leverage, implying that these institutional investors do not bet against beta. In addition, we explore its explanation using a holdings-based calendar-time portfolio approach and find that these institutional investors' low-beta portfolio does not outperform their high-beta portfolio. Overall, our results suggest that betting-against-beta strategy does not exist.

In the third essay, we investigate the relation between cash holdings and market concentration in the U.S. property-liability insurance industry. We leverage the highly disaggregated nature of insurer statutory data to construct a refined market concentration measure, market space weighted concentration, which more accurately reflects an insurer's state-line market space. Through our empirical analysis, we provide evidence in support of the predation risk theory. Specifically, insurers exposed to higher market concentration tend to hold more cash, and their cash is used to support future growth by reducing predation risk.

DEDICATION

To my advisor Andre P. Liebenberg,

who always encourages me.

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ESSAY I

PORTFOLIO CHOICE: FAMILIARITY, HEDGING, AND INDUSTRY BIAS

INTRODUCTION

The basic assumptions of the capital asset pricing theory imply that investors should hold well-diversified portfolios (e.g., Blume and Friend, 1975). However, a vast literature has documented that investors underdiversify and tilt their portfolios toward certain assets[1]. This portfolio tilt is generally referred to as a portfolio bias. For example, a well-known portfolio bias is "local bias" (or "home bias"), which implies that investors have a preference for local companies' stocks. Aside from local bias, previous studies also show that in the presence of non-financial income, investors tend to overweigh stocks to which they are industrially close (e.g., Massa and Simonov, 2006; Døskeland and Hvide, 2011)[2]. This portfolio bias is named "industry bias" (Van Nieuwerburgh and Veldkamp, 2009). Prior literature proposes competing theories in predicting the direction of the industry bias and provides mixed evidence for the driving force of the industry bias. In this study, we examine the direction and nature of industry bias in the common stock portfolios of U.S. Property-Liability (PL) insurers, who have considerable non-financial income and are also exposed to substantial non-financial income risk.

Massa and Simonov (2006) propose two competing theories regarding the different directions of the industry bias: the familiarity-based theory and the hedging-based theory. In terms of the familiarity-based theory, it argues that investors prefer stocks that they are familiar

[1] See Blume and Friend (1975), Cooper and Kaplanis (1994), Barber and Odean (2000), Grinblatt and Keloharju (2001), Ivković and Weisbenner (2005), Calvet, Campbell, and Sodini (2007), Lee, Liu, and Zhu (2008), Seasholes and Zhu (2010), Keloharju, Knüpfer, and Linnainmaa (2012), Keloharju, Knüpfer, and Linnainmaa (2012), and Von Gaudecker (2015).

[2] For individual investors, Massa and Simonov (2006) call industrially close stocks "professionally close stocks", and Døskeland and Hvide (2011) also call them "expertise stocks".

with, implying that in the presence of non-financial income, investors should tilt toward industrially close stocks. Given that the portfolio bias is widely quantified by the deviations from the market portfolio (i.e., the difference between the portfolio weight and the market weight) in the literature[3], a portfolio tilt toward industrially close stocks implies a positive industry bias. Massa and Simonov (2006) also distinguish between two types of familiarity, information-based familiarity (which is due to asymmetric information) and pure familiarity (which is due to behavioral bias). In contrast to the familiarity-based theory, the hedging-based theory is based on investors' motive for hedging their non-financial income risk. It posits that investors should tilt their portfolios toward assets with a negative correlation with their non-financial income and away from the assets with a positive correlation. In addition, the higher the risk of the non-financial income, the more investors will hedge. Massa and Simonov (2006) show that the correlation between investors' non-financial income and financial income increases with the industrial proximity. Therefore, the hedging-based theory suggests that investors should tilt away from the industrially close stocks, implying that the industry bias should be negative.

There is a paucity of empirical studies on industry bias in the literature. One important reason is that this research requires data of both investors' investment portfolio and their non-financial income. Massa and Simonov (2006) test their theories using Swedish individual investors' data[4]. They show that individual investors do not hedge but deliberately tilt their portfolios toward stocks that are close to their industry, indicating a positive industry bias. So they find evidence in support of the familiarity-based theory. Massa and Simonov (2006) also explore the nature of familiarity and find evidence that the familiarity is driven by information. They show that the familiarity differs across investors with different degrees of informativeness

[3] See Seasholes and Zhu (2010), Van Nieuwerburgh and Veldkamp (2009), and Døskeland and Hvide (2011).
[4] The data ocover detailed information on individual investors' holdings and their different sources of income, demographics, and family characteristics.

(which is represented by investors' wealth) and high wealth investors make more profits than low wealth investors. Additionally, they find that familiarity changes following a shock in investors' industrial proximity to the stocks. Specifically, when an investor has changed the industry in which he (she) is employed or has been unemployed recently, the investor's holdings will be less subject to an industry bias.

Døskeland and Hvide (2011) also investigate the existence and implications of the industry bias. Specifically, they use Norwegian individual investors as their research setting[5]. Consistent with Massa and Simonov (2006), they also report a positive industry bias, which supports the familiarly-based theory. However, they adopt a different approach to examine the nature of the familiarity. They argue that the information-based familiarity is expected to generate abnormal returns, while the pure familiarity is not. So they form transactions-based calendar-time portfolios to explore the information content in individual investors' investments in the close industries. They find that the abnormal returns from investing in industrially close stocks are negative, in many cases statistically significant. Therefore, Døskeland and Hvide (2011) argue that the positive industry bias is driven by a behavioral bias rather than asymmetric information.

While prior literature on individual investors supports the familiarity-based theory, the driving force of the familiarity remains inconclusive. In addition, investors that have non-financial income consist of not only individual investors but also institutional investors such as insurers and commercial banks. Since these institutional investors are exposed to substantial non-financial income risk and they are more sophisticated than individual investors, institutional investors' investment portfolios are a better setting to test the theories. In the presence of non-

[5] Døskeland and Hvide (2011) employ the data that cover the common stock holdings and transactions of all Norwegian individual investors at the Oslo Stock Exchange (OSE) and supplement these investment data with information on sociodemographic characteristics of each investor obtained from the government statistical agency.

financial income, do institutional investors' portfolios also exhibit an industry bias? If so, is the industry bias driven by familiarity or hedging? If the industry bias is driven by familiarity, is the familiarity due to asymmetric information or a behavioral bias? If the industry bias is driven by hedging, is the degree of hedging closely related to their non-financial income risk?

To answer these questions, we leverage the unique reporting requirements of firms in the U.S. Property-Liability (PL) insurance industry and use the common stock portfolios of PL insurers as our research setting. In this study, we classify the stocks in PL insurers' industry (i.e., PL insurance industry) as their industrially close stocks. Through empirical analysis, we find evidence for both the familiarity-based theory and the hedging-based theory. Specifically, we find that PL insurers exhibit a negative industry bias by tilting their common stock portfolios away from their industry. Using a transactions-based calendar-time portfolio approach, we find that PL insurers have information advantages in investing in industrially close stocks, supporting the information-based familiarity. We also show that their non-financial income risk (i.e., underwriting risk) leads to a portfolio tilt away from their industry, providing direct evidence in support of the hedging motive. Therefore, we conclude that PL insurers' hedging motive dominates familiarity in their portfolio allocation, even though they possess asymmetric information in the PL insurance industry.

The common stock portfolios of PL insurers are an ideal empirical setting to examine the investors' industry bias for the following reasons. First, both underwriting and investing are important considerations in insurers' operations. Since underwriting provides non-financial income for insurers to invest, the characteristics of underwriting can influence their portfolio choice. For example, Che and Liebenberg (2017) find that the more diversified an insurer's underwriting business, the more risky assets it will take in its investment portfolio. Therefore, the existence of underwriting activities satisfies the fundamental requirement (i.e., the presence of non-financial income) to test the theories of Massa and Simonov (2006). Second, the regulatory reporting requirements for insurance firms provide us with rich financial and investment data. Specifically, all licensed insurers are required to file their statutory statements on an annual basis. Similar to the 10-Ks filed by public firms in the unregulated industries, insurers' annual statutory statements report financial information on assets, liabilities, income, expenses, cash flows, etc., by which we are able to accurately measure their firm characteristics and more importantly, quantify their non-financial income risk. In addition, insurers are required to disclose highly detailed and disaggregated information on their investments. For example, Schedule D in insurers' annual statutory statements report insurers' common stock holdings at year end and transactions on each day. Third, we choose to study PL insurers rather than other regulated financial institutions that also earn non-financial income because PL insurers have substantial investments in common stocks. According to the Insurance Fact Book 2017 published by the Insurance Information Institute (I.I.I.) (2017), PL insurers' common stock portfolio ($326.2 billion) represents 21.30 percent of their total investments ($1.5 trillion) in 2015. By contrast, Life-Health (LH) insurers' and commercial banks' investment in common stocks is much smaller[6].

Our study contributes to the literature in two ways. First, we find empirical evidence that hedging plays an important role in shaping the industry bias. To our knowledge, our study is the first in the literature that provides evidence in support of the hedging-based theory. Second, we confirm the information advantage of investors in investing in their own industry. Our study is

[6] As is reported by Insurance Fact Book 2017, LH insurers' common stock portfolio ($75.2 billion) accounts for just 2.03 percent of their total investments ($3.7 trillion) in 2015. According to the Financial Services Fact Book 2013 published jointly by the I.I.I. and the Financial Services Roundtable (FSR) (2013), commercial banks' equity securities ($12.9 billion) represent 0.51 percent of all securities held in their investment portfolios ($2.54 trillion) in 2011.

also the first in the literature that supports the information-based familiarity from the perspective of abnormal returns.

The remainder of this study is as follows. The “Literature Review” summarizes the prior literature. The “Hypotheses Development” section presents the hypotheses that we test in this study. Next, the “Empirical Method” section discusses the methods that we employ in the following empirical analysis. The “Industry Bias” section reports the results from the examination of the industry bias. The “Investigation on Familiarity” section presents the results from the analysis of the nature of the familiarity. Then the “Investigation on Hedging” section reports the results from the test of the hedging-based hypothesis. Last, the “Conclusion” section concludes our study.

LITERATURE REVIEW

Prior literature has widely investigated suboptimal portfolio structure, more commonly referred to as underdiversification. Blume and Friend (1975) conduct the seminal work on this research. They find that a large number of households do not hold the market portfolio of risky assets in conjunction with risk-free assets and that their portfolios are poorly diversified. Blume and Friend (1975) argue that the possible cause of portfolio underdiversification is the heterogeneity of investors' expectations. Barber and Odean (2000) examine the common stock investments of households at a large discount brokerage. They show that households tilt their portfolios toward small value stocks with high market risk and that the net performance is poor. They suggest that the underperformance can be explained by overconfidence. Von Gaudecker (2015) investigates the portfolio diversification and performance of Dutch households. He employs the return loss[7] as the diversification measure and finds that the large losses from underdiversification are incurred by those investors who neither turn to external help nor have good skills. His study suggests that the underdiversification reflects investment mistakes rather than optimal strategies. Aside from the general underdiversification, a stream of literature examines some specific portfolio biases.

One important type of portfolio bias is local bias, which means that investors have a preference for local stocks. Cooper and Kaplanis (1994) examine whether local bias in international investment portfolios is caused by the motive to hedge inflation risk. They find that

[7] The return loss refers to "the difference between the maximum expected return attainable at a given standard deviation and the actual expected return for a particular portfolio" (Von Gaudecker, 2015, page 490).

the local bias cannot be explained by inflation hedging unless investors have low levels of risk aversion and equity returns are negatively related to domestic inflation. Grinblatt and Keloharju (2001) document that Finnish investors exhibit a preference for nearby firms and for same-language and same-culture firms. They also show that the marginal effect of distance is less for nationally known companies, for long distances, and for diversified investors. Ivković and Weisbenner (2005) investigate whether the local bias is driven by asymmetric information and find that the local holdings outperform nonlocal holdings, implying that investors are able to process locally available information to earn excess returns. Seasholes and Zhu (2010) also test whether individual investors have asymmetric information about local stocks, but they use a different method that addresses four pitfalls arising from studying individuals' portfolios. They show that local holdings do not generate abnormal returns and the purchases of local stocks underperform the sales of local stocks, implying that individuals do not have value-relevant information about local stocks.

Prior literature has also presented other types of portfolio bias. For example, Lee, Liu, and Zhu (2008) document a portfolio bias toward the stocks of investors' employers. They show that this portfolio bias incurs significant economic costs. Their study suggests that the behavioral bias is the possible cause. Keloharju, Knüpfer, and Linnainmaa (2012) examine whether individuals' product market choices influence their investment decisions. They find that investors are more likely to purchase and less likely to sell the shares of firms that they buy products from and the customer relation is positively related to the ownership stake.

While the portfolio bias is widely documented in the finance literature, limited studies have paid attention to the industry bias, and the driver of the industry bias remains inconclusive.

We discuss the two studies on the industry bias while developing our hypotheses in the following section.

HYPOTHESES DEVELOPMENT

Massa and Simonov (2006) propose two theories that explain industry bias – familiarity and hedging. While these theories are competing, they are not mutually exclusive and may both play a role in shaping overall industry bias. The familiarity-based theory posits that investors prefer industrially close stocks due to familiarity, leading to a positive industry bias. Consistent with this theory, Massa and Simonov (2006) find empirical evidence that Swedish individual investors deliberately tilt their portfolios toward industrially close stocks. Using the percentage of the market portfolio in an industry as the benchmark, Døskeland and Hvide (2011) also show that Norwegian individual investors overweight industrially close stocks in their portfolios. Therefore, in our setting of PL insurers, if the familiarity-based theory holds, we would expect that PL insurers tilt their common stock portfolios toward industrially close stocks (i.e., stocks of Property-Liability insurers), implying a positive industry bias. This hypothesis is described as follows,

H1 (Familiarity-Based Hypothesis): *PL insurers tilt their portfolios toward industrially close stocks.*

Massa and Simonov (2006) decompose familiarity into two different types, each of them with distinct implications. One type of familiarity is driven by asymmetric information. That is, investors have limited awareness or knowledge of all stocks, and information about a particular stock induces investors to invest more in it. They name this type of familiarity information-based familiarity. In the setting of industrial portfolio allocation, investors have a preference for industrially close stocks because industrial proximity provides an inexpensive route through which investors have a comparative advantage in collecting information (Døskeland and Hvide, 2011). Døskeland and Hvide (2011) also argue that if the familiarity is driven by asymmetric information, one would expect that investors who tilt their portfolios toward industrially close stocks earn abnormally high returns. In our study, if the familiarity is attributable to the asymmetric information, we would expect that PL insurers earn positive abnormal returns on their industrially close stocks. We summarize this hypothesis as follows:

H1.1 (Information-Based Familiarity Hypothesis): *PL insurers earn positive abnormal returns on their investment in industrially close stocks.*

The other type of familiarity is driven by a behavioral bias. Massa and Simonov (2006) refer to this familiarity as pure familiarity. They argue that this behavioral bias is caused by the saliency or availability of information. Specifically, investors erroneously rely on salient or often mentioned information rather than value-relevant information that is blended in the background. Døskeland and Hvide (2011) also consider overconfidence another source of behavioral bias. They argue that overconfident investors overestimate the precision of their information about future returns of securities, and this miscalibration causes heterogeneity in investors' opinions, which induces them to trade (Odean, 1998). In contrast to the information-based familiarity, the pure familiarity is not expected to generate abnormal returns. In our setting, if the familiarity is attributable to the behavioral bias, we would expect that PL insurers do not earn abnormal returns on their industrially close stocks. The above discussion leads to the following hypothesis:

H1.2 (Pure Familiarity Hypothesis): *PL insurers do not earn abnormal returns on their investment in industrially close stocks.*

An alternative to the familiarity-based theory of the industry bias is the hedging-based theory. Massa and Simonov (2006) argue that in the presence of non-financial income, investors should hedge their non-financial income risk by tilting their portfolios toward assets with a negative correlation with their non-financial income and away from the assets with a positive correlation. They also show that the correlation between investors' non-financial income and financial income increases with the industrial proximity. Therefore, contrary to the familiarity-based theory, if investors' hedging motive dominates, they will tilt their portfolios away from the industrially close stocks, leading to a negative industry bias. In our setting of PL insurers, this hypothesis is summarized as follows:

H2 (Hedging-Based Hypothesis): *PL insurers tilt their portfolios away from industrially close stocks.*

Additionally, Massa and Simonov (2006) posit that the tilt in the risk profile should be positively related to the non-financial income risk. In other words, the higher the risk of the non-financial income, the more investors will hedge. For PL insurers, their non-financial income risk is the underwriting risk. So if the hedging-based theory holds, their portfolio tilt away from the industrially close stocks should increase as the underwriting risk increases. We propose this hypothesis as follows:

H2.1 (Hedging-Risk Hypothesis): *PL insurers' portfolio tilt away from industrially close stocks is driven by their underwriting risk.*

METHODOLOGY

Industry Bias Measure

To test the familiarity-based hypothesis and hedging-based hypothesis, we need to identify the industry bias regarding the industrially close stocks in PL insurers' portfolios. PL insurers have their clearly defined SIC code at the four-digit level (i.e., 6331) (e.g., Ke, Petroni, and Safieddine, 1999) [8]. Therefore, we classify the stocks in the PL insurance industry as industrially close stocks for PL insurers. The portfolio bias has been investigated by many studies. The most widely used measure is the excess weight on the certain stocks that investors tilt their portfolios toward (e.g., Seasholes and Zhu, 2010; Døskeland and Hvide, 2011). Following Seasholes and Zhu (2010), we also scale the excess weight by the percentage of the market portfolio in these stocks. So our measure of the industry bias (IB) is calculated as follows,

$$IB = \frac{w_p - w_m}{w_m} \tag{1}$$

where w_p represents the percentage of a PL insurer's portfolio in the PL insurance industry and w_m represents the percentage of the market portfolio in the PL insurance industry[9].

[8] The Fama-French 48 Industry Classifications consider both 6330 and 6331 as the SIC codes for PL insurers because they cover the data in early years. However, 6330 was removed from the SIC codes in an historical change and has not been used to classify companies' industries any more. We also search in the Compustat database and find no firm assigned to an SIC code 6330 in our sample period (i.e., 2001-2015). So, we follow the literature (e.g., Ke, Petroni, and Safieddine,1999) and use only 6331 to identify PL stocks.

[9] As a robustness check, we also use other measures for the industry bias. Specifically, following Seasholes and Zhu (2010) and Døskeland and Hvide (2011), we measure the industry bias by the unscaled excess weight (i.e., $w_p - w_m$). Also, following Van Nieuwerburgh and Veldkamp (2009), we measure the industry bias by the excess weight scaled by the percentage of the market portfolio in the other stocks (i.e., $(w_p - w_m)/(1 - w_m)$). We conduct our following analysis using these alternative measures, and we find that our results are qualitatively the same.

Investigation of Familiarity

To investigate the nature of the familiarity, following Seasholes and Zhu (2010) and Døskeland and Hvide (2011), we use the abnormal returns (or "Alpha") from PL insurers' transactions-based calendar-time portfolios as an indicator of asymmetric information and test whether PL insurers' trades of their industrially close stocks earn superior returns. We employ the Alpha in the asset pricing model as an indicator of asymmetric information. If the Alpha is positive and significant, the information-based familiarity hypothesis will be supported. Otherwise, the pure familiarity hypothesis will be supported.

The transactions-based calendar-time portfolios approach employs the transactions data and mimics the buys and sells by forming "Buys" and "Sells" calendar-time portfolios. Each time a PL insurer buys (sells) a stock in the PL insurance industry, we place the same number of shares in the calendar-time "Buys" ("Sells") portfolio at the end of the day. We follow a buy-and-hold strategy and assume that the shares will be held in the portfolio for 3 months, 6 months, 9 months, and 12 months, respectively. We calculate the value-weighted returns on the "Buys" portfolio and the "Sells" portfolio and regress the return difference between these two portfolios ("Buys-minus-Sells") of all PL insurers ($R_z^{Buys} - R_z^{Sells}$) on the excess market return ($R_m - R_f$) and the Fama-French factors (i.e., SMB and HML) or the Fama-French-Carhart factors (i.e., SMB, HML, and MOM). The models for the regressions are as follows,

$$R_z^{Buys} - R_z^{Sells} = \alpha + \beta_1(R_m - R_f) + \beta_2 SMB + \beta_3 HML \qquad (2)$$

$$R_z^{Buys} - R_z^{Sells} = \alpha + \beta_1(R_m - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 MOM \qquad (3)$$

The significance of the Alpha is tested by a t-test that is based on Newey-West standard errors with five lags and robust to heteroskedasticity and serial correlation of residuals.

Investigation of Hedging

To test the hedging-risk hypothesis, we examine the relation between the portfolio tilt regarding the industrially close stocks and the underwriting risk. We use the proportion of investment (w_p) and the industry bias (IB) in the PL insurance industry as the dependent variables. Since the proportion is bounded to the range from 0 to 1 and the industry bias is bounded to the range from -1 to $(1-w_m)/w_m$, we employ the Tobit model with random effects[10]. Apart from the Tobit model, we also use Heckman's (1979) two-stage procedure in order to incorporate insurers' firm fixed effects[11]. The regression model can be written as follows,

$$w_p \text{ } or \text{ } IB = f(UND\_RISK, Controls) \tag{4}$$

Consistent with Ho, Lai, and Lee (2013) and Han, Lai, and Ho (2015), we measure underwriting risk (UND_RISK) by the rolling standard deviation of underwriting loss ratio over the previous five years, and the underwriting loss ratio is defined as a ratio of losses incurred and loss adjustment expenses to premiums earned.

Prior literature that investigates the role of investor characteristics in determining portfolio choice predominately focuses on individual investors because the proprietary data of individual investors make it possible to observe both the investors' investment and their background (e.g., Massa and Simonov, 2006; Døskeland and Hvide, 2011; Keloharju, Knüpfer, and Linnainmaa, 2012). However, few studies investigate the effects of firm characteristics on institutional investors' portfolio choice. Therefore, we apply the available control variables for

[10] In econometrics, a sufficient statistic that allows firm fixed effects to be conditioned out of likelihood does not exist. Therefore, we need to choose between a pooled regression model and a random effect model. We perform a likelihood-ratio test, and the results from the test suggest that the random effects should be included in the model.

[11] In the first stage, we model the decision to invest in the PL insurance industry as a function of the explanatory variables that appear in the second stage and the correlation between the PL insurers' non-financial income (measured by underwriting loss ratio) and the market portfolio. In the second stage, we regress the proportion of investment or the industry bias on a vector of explanatory variables and Heckman's lambda. Additionally, we control for the firm fixed effects in the second stage.

individuals to institutions in our multivariate regression analysis. Following Døskeland and Hvide (2011), our controls consist of the industry experience, gross wealth, income, listing status of the investor's company, market value of the stock portfolio, portfolio diversification, and the number of stocks in the industry. Specifically, we measure the industry experience by the firm age (AGE), which is calculated as natural logarithm of the number of years since commencement, measure the gross wealth by the firm size ($SIZE$), which is calculated as the natural logarithm of total net admitted assets, and measure the income by the size of net premiums written (NPW_SIZE), which is calculated as the natural logarithm of total net premiums written. The listing status is measured by a dummy variable ($PUBLIC$) that is equal to 1 for a publicly-traded insurer and 0 for a private insurer. The market value of common stock portfolio (PTF_MV) is measured by the natural logarithm of total market value of common stock holdings. Portfolio diversification (PTF_DIV) is measured by the natural logarithm of the number of stocks held by the insurer. To control for the number of stocks in the industry at the end of each year and all other unobservable year-specific factors, we include the year fixed effects in the model.

Ho, Lai, and Lee (2013) also provide several explanatory variables that can affect insurers' investment risk taking. Following Ho, Lai, and Lee (2013), we also control for the organization form, reinsurance usage, long-tail insurance, business line diversification, and geographic diversification. Specifically, the organization form ($MUTUAL$) is a dummy variable that is equal to 1 for a mutual insurer and 0 for a stock insurer. Reinsurance usage ($REINSURANCE$) is measured by the reinsurance ratio, which is calculated as the ratio of premiums ceded to the sum of direct premiums written and reinsurance assumed. The weight of long-tail insurance ($LONG\_TAIL$) is the percentage of net premiums written on long-tail lines[12]. Following Berry-Stölzle, Liebenberg, Ruhland, and Sommer (2012), the business line diversification ($LINES\_DIV$) is calculated as the complement of the Herfindahl Index of net premiums written (NPW) across 24 lines of business[13]. The calculation is shown as follows:

$$LINES\_DIV_{i,t} = 1 - \sum_{j=1}^{24} \left(\frac{NPW_{i,j,t}}{NPW_t}\right)^2 \tag{5}$$

where $NPW_{i,j,t}$ denotes the net premiums written by insurer i in line $j = 1, \dots, 24$ in year t, and $NPW_{i,t}$ denotes the total net premiums written by insurer i in a given year t. Larger values of $LINES\_DIV_{i,t}$ represent higher levels of diversification. Following Liebenberg and Sommer (2008), we measure the geographic diversification measure (GEO_DIV) by the complement of the Herfindahl Index of direct premiums written (DPW) across 58 states and territories[14]. Its calculation is as follows:

$$GEO\_DIV_{i,t} = 1 - \sum_{k=1}^{58} \left(\frac{DPW_{i,k,t}}{DPW_{i,t}}\right)^2 \tag{6}$$

where $DPW_{i,k,t}$ denotes the direct premiums written by an insurer i in state $k = 1, \dots, 58$ in year t, and $DPW_{i,t}$ denotes the total direct premiums written in a given year t. Since the U.S. insurance industry is regulated by each state, we control for the state fixed effects to deal with the unobservable and potential effects of state regulations. In addition, insurers operating in different

[12] Consistent with Phillips, Cummins, and Allen (1998), long-tail lines include Ocean Marine, Medical Professional Liability, International, Reinsurance, Workers' Compensation, Other Liability, Product Liability, Aircraft, Boiler and Machinery, Farmowners Multiple Peril, Homeowners Multiple Peril, Commercial Multiple Peril, and Automobile Liability. Short-tail lines include the following: Inland Marine, Financial Guaranty, Earthquake, Fidelity, Surety, Burglary and Theft, Credit, Fire and Allied Lines, Mortgage Guaranty, and Automobile Physical Damage.

[13] Following Berry-Stölzle et al. (2012), we group similar business lines into 24 distinct lines written by PL insurers: Accident and Health, Aircraft, Auto, Boiler and Machinery, Burglary and Theft, Commercial Multiple Peril, Credit, Earthquake, Farmowners' Multiple Peril, Financial Guaranty, Fidelity, Fire and Allied lines, Homeowners' Multiple Peril, Inland Marine, International, Medical Professional Liability, Mortgage Guaranty, Ocean Marine, Other, Other Liability, Products Liability, Reinsurance, Surety, and Workers' Compensation.

[14] We obtain premiums written across states and territories from Schedule T of the NAIC Annual Statements.

business lines may have different risk appetite. So we also include the line fixed effects in our regressions.

DATA AND SAMPLE

We obtain the common stock holdings and transactions (i.e., buys and sells) data of PL insurers from the NAIC InfoPro database for the years 2001[15] through 2015. Our data cover the common stocks of unaffiliated firms on Schedule D (Parts 2 – 5) of PL insurers' annual statutory statements. We delete stock holdings, buys, and sells with non-positive number of shares or value[16] and aggregate the data of the same stock for each insurer on each portfolio date (i.e., year-end) or transaction date. The stock information (e.g., price, cumulative factor, SIC codes, returns) is obtained from the CRSP database and merged with our stock holdings and transactions data. Specifically, stock holdings are merged with the their most recent[17] stock information in each year, and stock buys and sells are merged with their stock information on each transaction date. We remove the stocks in our data that cannot be merged with the CRSP database. Because we focus on the industry bias, the industry classification of each stock is needed for our study. We obtain the Fama-French 48 Industry Classification from Kenneth R. French's website and remove stocks that do not have an SIC code in their classification.

[15] We choose 2001 as our starting year because before 2001, the transaction dates are recorded as "VARIOUS" in the Schedule D of insurers' statutory statements if a stock is traded on multiple different dates. Therefore, we are unable to identify the transaction dates for these stocks, which are needed by our transactions-based calendar-time portfolios.

[16] For stock holdings, the value refers to the fair value. For stock buys, the value refers to the actual costs. For stock sells, the value refers to the adjusted carrying value.

[17] The purpose of merging stock holdings with the CRSP database is to get the SIC code for industry classification, and a stock's SIC code does not change often in a year. Therefore, if a stock's information is not available on the last trading day in a year, its most recent information in that year is used.

The detailed data screening process and the number of observations remaining in our sample following each step are reported in panels A, B, and C of Table 1. Our stock holdings sample includes 956,302 insurer-stock-year observations, our stock buys sample includes 966,048 insurer-stock-day observations, and our stock sells sample includes 896,040 insurer-stock-day observations. Table 2 reports the time series average of stock holdings, buys, and sells, respectively, across all years in the sample period. We find that on average, PL insurers' holdings of publicly traded common stocks are \$133.30 billion, stock buys are \$32.80 billion, and stock sells are \$27.20 billion.

In our investigation of familiarity with the transactions-based calendar-time portfolios, we obtain the risk-free rate, Fama-French factors (i.e., SMB and HML) and the Carhart momentum factor (i.e., MOM) from Kenneth R. French's website.

In our analysis of the hedging motive, we also obtain the financial data of PL insurers from the NAIC InfoPro database. We exclude insurers with non-positive total net admitted assets, net premiums written, and an organizational form other than stock or mutual (e.g., Che and Liebenberg, 2017). We also exclude insurers with a non-positive market value of common stock portfolio. We find that many observations drop out of the sample because a significant number of insurers do not invest in publicly traded common stocks. Finally, we remove insurers that do not have sufficient information to calculate the variables in our hedging analysis. The data screening process is described in panel D of Table 1. Our final sample for the hedging analysis consists of 5,843 insurer-year observations. The sample represents, on average, 45.94 percent (54.16 percent) of the entire U.S. PL insurance industry in terms of the net admitted assets (net premiums written) across all years during our sample period. In addition, we winsorize the underwriting risk and the reinsurance ratio at the 1st percentile and the 99th percentile level to reduce the potential effects of outliers[18]. The summary statistics are presented in the "Hedging" section.

[18] We detect the outliers by a scatter plot and the Cook's distance test. Both suggest that outliers are present in our values of the underwriting risk and the reinsurance ratio.

Table 1
Data Screen

	Screen Criteria	Number of Observations
Panel A: Stock Holdings (Insurer-Stock -Year Observations)		
(i)	Obtain PL insurers' stock holdings (unaffiliated) from the NAIC InfoPro database (Schedule D-Part 2-Section 2) (2001-2015).	1,292,954
(ii)	Remove stock holdings with non-positive number of shares or fair value.	1,279,602
(iii)	Aggregate holdings of the same stocks for each insurer on each portfolio date (year-end) for each PL insurer.	1,184,395
(iv)	Remove stock holdings that cannot be merged with the CRSP database (most recent information in each year).	968,761
(v)	Remove stocks holdings without an SIC code in Fama-French 48 Industry Classification.	956,302
Panel B: Stock Buys (Insurer-Stock -Day Observations)		
(i)	Obtain PL insurers' stock buys (unaffiliated) from the NAIC InfoPro database (Schedule D-Part 3 and Part 5) (2001-2015).	1,394,770
(ii)	Remove stock buys with non-positive number of shares or actual costs.	1,351,234
(iii)	Aggregate buys of the same stocks for each insurer on each transaction date for each PL insurer.	1,229,701
(iv)	Remove stocks buys that cannot be merged with the CRSP database on each transaction date.	980,179
(v)	Remove stocks buys without an SIC code in Fama-French 48 Industry Classification.	966,048
Panel C: Stock Sells (Insurer-Stock -Day Observations)		
(i)	Obtain PL insurers' stock sells (unaffiliated) from the NAIC InfoPro database (Schedule D-Part 4 and Part 5) (2001-2015).	1,474,635
(ii)	Remove stock sells with non-positive number of shares or adjusted carrying value.	1,417,644
(iii)	Aggregate sells of the same stocks for each insurer on each transaction date for each PL insurer.	1,150,677
(iv)	Remove stock sells that cannot be merged with the CRSP database on each transaction date.	907,963
(v)	Remove stock sells without an SIC code in Fama-French 48 Industry Classification.	896,040
Panel D: Financial Data (Insurer-Year Observations)		
(i)	Obtain PL insurers' financial data from the NAIC InfoPro database (2001-2015).	19,371
(ii)	Remove PL insurers with non-positive net admitted assets.	19,370
(iii)	Remove PL insurers with non-positive net premiums written.	17,030
(iv)	Remove PL insurers with non-positive market value of a common stock portfolio.	7,280
(v)	Remove PL insurers that are neither mutuals nor stocks.	6,347
(vi)	Remove PL insurers without sufficient information to calculate the variables in the hedging analysis.	5,843

This table presents the data screenings in our samples. Panel A, B, C, and D report the screen criteria and number of observations in the sample of stock holdings, stock buys, stock sells, and financial data respectively.

Table 2
Summary Statistics of Stock Holdings and Transactions

	Number of PL Insurers (1)	All Stocks (2)	PL Insurance Stocks (3)	PL Insurance Stocks (4) = (3)/(2)	Other Stocks (5)	Other Stocks (6) = (5)/(2)
Panel A: Stock Holdings						
Num of Stocks	948	3,320.47	50.73	1.53%	3,269.73	98.47%
Num of Shares (billion)	948	3.02	0.02	0.65%	3.00	99.35%
Value ($ billion)	948	133.30	1.36	1.02%	131.94	98.98%
Panel B: Stock Buys						
Num of Transactions (thousand)	863	64.40	0.97	1.52%	63.43	98.48%
Num of Stocks	863	3,228.53	49.40	1.52%	3,180.80	98.53%
Num of Shares (billion)	863	0.90	0.01	1.08%	0.89	98.92%
Value ($ billion)	863	32.80	0.43	1.40%	32.37	98.60%
Panel C: Stock Sells						
Num of Transactions (thousand)	854	59.74	0.93	1.55%	58.81	98.45%
Num of Stocks	854	3,227.93	50.20	1.55%	3,179.47	98.50%
Num of Shares (billion)	854	0.86	0.01	1.33%	0.85	98.67%
Value ($ billion)	854	27.20	0.43	1.56%	26.77	98.44%

This table presents the summary statistics of PL insurers' holdings and transactions (i.e., buys and sells) of publicly traded common stocks. Panels A, B, and C report the time series average of stock holdings, buys, and sells, respectively, across all years in the sample period (2001-2015).

INDUSTRY BIAS

We present the results for the industry bias in Table 3. Table 3 reports that the average percentage of PL insurers' portfolio in PL stocks across all insurer-year observations is 2.11 percent, while the average percentage of the market portfolio across all years in the sample period in PL stocks is 2.64 percent. The mean of the industry bias is -20.67%, and it is statistically significant. The median is -100.00%, implying that more than half of the insurers in our sample do not invest in their industry. Overall, we find that contrary to the findings in the prior studies on individual investors, PL insurers exhibit a negative industry bias by tilting their portfolios away from industrially close stocks. The negative industry bias supports the hedging-based hypothesis. Therefore, we find initial evidence for the hedging-based theory.

Table 3
Industry Bias

	w_p	w_m	Industry Bias (IB) $(w_p - w_m)/w_m$	*p-value*
Mean	2.11%	2.64%	-20.67%	0.00
Median	0.00%	2.59%	-100.00%	0.00

This table presents the industry bias in the stock holdings of PL insurers. The industry bias (IB) is measured by $(w_p - w_m)/w_m$, where w_p represents the percentage of a PL insurer's portfolio in the PL insurance industry and w_m represents the percentage of the market portfolio in the PL insurance industry. The significance of the mean is tested by a t-test with its p-value reported. The significance of the median is tested by a Wilcoxon rank sum test with its p-value reported. The table also reports the mean and the median of w_p across all insurer-year observations and w_m across all years in the sample period.

FAMILIARITY

In the above section, we find evidence in favor of the hedging-based theory. However, it is unknown whether the industry bias is purely a product of hedging or a net effect of both familiarity and hedging. To answer this question, we first assume that the familiarity also plays a role in shaping the industry bias and then examine the nature of familiarity. If we find that PL insurers have asymmetric information in investing in their industry, both our initial assumption and the information-based familiarity will be supported, implying that the negative industry bias reflects a net effect of hedging and familiarity. To investigate the asymmetric information, we employ the transactions-based calendar-time portfolios to identify the abnormal returns in PL insurers' trades. The variables in our regression models are defined in Table 4.

Table 5 reports the results from our transactions-based calendar-time portfolios. We find that when the holding period is 3 months, 6 months, and 9 months, the daily abnormal return (i.e., Alpha) for holding PL stocks is positive and significant in both the Fama-French 3-Factor model and the Carhart 4-Factor model. Specifically, the Alpha is reported to be 0.02 percent or 0.03 percent, which can be translated into an annual return of roughly 5 percent or 8 percent, respectively. However, the Alpha is not significant when the holding period is 12 months. The insignificant Alpha in a longer holding period supports the phenomenon of Alpha decay found by Di Mascio, Lines, and Naik (2015) and is expected. In the unreported tables, we do not find a significant Alpha when PL insurers trade stocks in the other industries regardless of the length of the holding period. Overall, we find that PL insurers have an information advantage in investing in stocks in the PL insurance industry. Therefore, the information-based familiarity plays a role in shaping the negative industry bias in PL stocks even though the net effect is driven by the hedging motive.

Table 4
Variables and Their Descriptions in Asymmetric Information Analysis

Variable Name	Variable Description
R_z^{Buys}-R_z^{Sells}	The return difference between the industry "Buys" portfolio and the industry "Sells" portfolio ("Buys-minus-Sells") of all PL insurers.
R_z^{Buys}	The value-weighted return of the industry "Buys" portfolio of all PL insurers.
R_z^{Sells}	The value-weighted return of the industry "Sells" portfolio of all PL insurers.
R_m-R_f	The excess market return for all stocks with an SIC code in Fama-French 48 Industry Classification.
R_m	The value-weighted market return for all stocks with an SIC code in Fama-French 48 Industry Classification.
R_f	The risk-free return. The data are obtained from Kenneth R. French's website.
SMB	The small-minus-big portfolio return. The data are obtained from Kenneth R. French's website.
HML	The high-minus-low (book-to-market) portfolio return. The data are obtained from Kenneth R. French's website.
MOM	The momentum (winners-minus-losers) portfolio return. The data are obtained from Kenneth R. French's website.

This table reports the variables and their descriptions in the asymmetric information analysis.

Table 5
Regressions with Transaction-Based Calendar-Time Portfolios

Dependent Variable: R_z^{Buys}-R_z^{Sells}								
Holding Period	3 Months		6 Months		9 Months		12 Months	
Variables	3-Factor	4-Factor	3-Factor	4-Factor	3-Factor	4-Factor	3-Factor	4-Factor
Alpha	0.0002*	0.0002*	0.0003***	0.0003***	0.0002**	0.0002**	0.0001	0.0001
(t-stat)	(1.8360)	(1.8023)	(2.6540)	(2.6423)	(2.0761)	(2.0149)	(1.3746)	(1.2591)
R_m-R_f	-0.0399**	-0.0356**	-0.0405**	-0.0394**	-0.0461***	-0.0400***	-0.0325**	-0.0219*
(t-stat)	(-2.4698)	(-2.4292)	(-2.4629)	(-2.5590)	(-3.1210)	(-2.9204)	(-2.3839)	(-1.6798)
SMB	0.0259	0.0238	0.0245	0.0240	0.0405*	0.0378	0.0213	0.0168
(t-stat)	(0.9559)	(0.8784)	(0.9028)	(0.8926)	(1.6761)	(1.5828)	(1.0270)	(0.8201)
HML	-0.0765	-0.0718	-0.0688	-0.0676	-0.0698	-0.0631	-0.0797*	-0.0679*
(t-stat)	(-1.5714)	(-1.6150)	(-1.4299)	(-1.5323)	(-1.6133)	(-1.6096)	(-1.9426)	(-1.8286)
MOM		0.0139		0.0036		0.0194		0.0341*
(t-stat)		(0.5938)		(0.1624)		(0.9582)		(1.8365)
N. of Obs.	3,830	3,830	3,890	3,890	3,950	3,950	4,010	4,010

This table reports results from regressions with transactions-based calendar-time portfolios with a holding period of 3 months, 6 months, 9 months, and 12 months, respectively. The regressions are based on the Fama-French 3-Factor model and the Carhart 4-Factor model. The dependent variable is the return difference between the PL insurance industry "Buys" portfolio and the PL insurance industry "Sells" portfolio ("Buys-minus-Sells") of all PL insurers. The other variables are defined in Table 4. The t-statistics are based on Newey-West standard errors with five lags and robust to heteroskedasticity and serial correlation of residuals. *, **, and *** denote significance at 10%, 5%, and 1% levels respectively.

HEDGING

While the negative industry bias provides initial evidence for the hedging-based theory, in this section, we attempt to provide more direct evidence for PL insurers’ motive for hedging. Specifically, we investigate whether PL insurers’ portfolio tilt away from industrially close stocks is positively related to their underwriting risk. The variables are defined in Table 6, and the summary statistics is presented in Table 7.

We employ two different dependent variables to test this relation. The first dependent variable that we use is the proportion of PL insurers’ investment portfolio in the PL insurance industry. The regression results are reported in Table 8. We find that the coefficient estimate on the underwriting risk is negative and significant in both the Tobit model and the Heckman model, implying that high underwriting risk leads PL insurers to tilt away from stocks in their industry. The second dependent variable we use is the industry bias. Table 9 presents the results. It shows that the coefficient estimate on the underwriting risk is negative and significant in both models. These findings are consistent with what we report in Table 8 and further support the hedging-risk hypothesis.

Taken together, we find that even though PL insurers have an information advantage with respect to trades of PL stocks, their exposure to underwriting risk results in a net portfolio tilt away from their own industry. Our results suggest that industry bias is a hybrid product of both familiarity and hedging, and that, for PL insurers, the hedging motive dominates the familiarity effect.

Table 6
Variables and Their Descriptions in Hedging Analysis

Variable Name	Variable Description
w_p	Proportion of the common stock portfolio in PL insurance stocks.
IB	Industry bias in PL insurance stocks.
UND_RISK	Underwriting risk, as measured by the rolling standard deviation of the loss ratio over the previous five years.
AGE	Firm age, as measured by the natural logarithm of the number of years since commencement.
SIZE	Firm size, as measured by the natural logarithm of total net admitted assets.
NPW_SIZE	Size of net premiums written, as measured by the natural logarithm of total net premiums written.
PUBLIC	Public status, as measured by a dummy variable that is equal to 1 for a publicly-traded insurer and 0 for a private insurer.
PTF_MV	Market value of common stock portfolio, as measured by the natural logarithm of the total market value of the common stock portfolio.
PTF_DIV	Portfolio diversification, as measured by the natural logarithm of the number of stocks held by the insurer.
MUTUAL	Organization form, as measured by the dummy variable that is equal to 1 for a mutual insurer and 0 for a stock insurer.
REINSURANCE	Reinsurance ratio, as measured by the ratio of premiums ceded to the sum of direct premiums written and reinsurance assumed.
LONG_TAIL	Weight of long-tail line insurance, as measured by the percentage of net premiums written on long-tail lines.
LINES_DIV	Business line diversification, as measured by the complement of the Herfindahl Index of net premiums written across all business lines.
GEO_DIV	Geographic diversification, measured by the complement of Herfindahl index of direct premiums written across all U.S. states and territories.

This table reports the variables and their descriptions in the hedging analysis.

Table 7
Summary Statistics for Hedging Analysis

Variable Name	N	Mean	Median	Min	Max	Std. Dev.	1st Quartile	3rd Quartile
w_p	5,843	0.0173	0.0000	0.0000	1.0000	0.0636	0.0000	0.0135
IB	5,843	-0.3393	-1.0000	-1.0000	40.8100	2.4251	-1.0000	-0.5004
UND_RISK	5,843	0.1530	0.0824	0.0105	3.1723	0.3357	0.0503	0.1386
AGE	5,843	3.7085	3.8067	0.0000	5.3706	0.9831	2.9957	4.6540
SIZE	5,843	17.7717	17.6543	11.5375	23.7304	1.7299	16.5383	18.9791
NPW_SIZE	5,843	16.5885	16.6905	5.5013	22.1558	1.9930	15.3491	17.9766
PUBLIC	5,843	0.0426	0.0000	0.0000	1.0000	0.2020	0.0000	0.0000
PTF_MV	5,843	14.6527	14.7492	1.0986	22.1642	2.3611	13.2816	16.2089
PTF_DIV	5,843	3.0987	3.4012	0.0000	7.2349	1.5534	2.0794	4.1109
MUTUAL	5,843	0.4528	0.0000	0.0000	1.0000	0.4978	0.0000	1.0000
REINSURANCE	5,843	0.2476	0.1899	0.0000	0.8732	0.2152	0.0779	0.3654
LONG_TAIL	5,843	0.6979	0.7934	0.0000	1.0000	0.3233	0.6024	0.9492
LINES_DIV	5,843	0.3565	0.4025	0.0000	0.8537	0.3008	0.0000	0.6510
GEO_DIV	5,843	0.3001	0.0838	0.0000	0.9650	0.3485	0.0000	0.6294

This table presents the summary statistics of the sample in the hedging analysis. All variables are defined in Table 6.

Table 8
Effects of Underwriting Risk on Proportion of Investment in PL Insurance Industry

Dependent Variable: Proportion of Investment in PL Insurance Industry (w_p)		
Model:	Tobit	Heckman
INTERCEPT	-0.4366***	-0.3221
	(0.0611)	(0.2675)
UND_RISK	-0.0180**	-0.0261***
	(0.0082)	(0.0081)
AGE	0.0015	0.0122
	(0.0061)	(0.0189)
SIZE	0.0187***	0.0220
	(0.0060)	(0.0159)
NPW_SIZE	0.0003	-0.0042
	(0.0047)	(0.0098)
PUBLIC	-0.0011	0.0337**
	(0.0205)	(0.0153)
PTF_MV	-0.0073***	-0.0221**
	(0.0025)	(0.0086)
PTF_DIV	0.0343***	0.0297***
	(0.0029)	(0.0101)
MUTUAL	-0.0084	-0.0424**
	(0.0111)	(0.0182)
REINSURANCE	-0.0369**	-0.0281
	(0.0165)	(0.0346)
LONG_TAIL	0.0056	0.0135
	(0.0167)	(0.0318)
LINES_DIV	-0.0482**	-0.0076
	(0.0223)	(0.0338)
GEO_DIV	0.0069	0.0162
	(0.0188)	(0.0314)
Lambda		0.1153***
		(0.0200)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	No	Yes
Line Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
N. of Obs.	5,843	2,094

This table presents the results from the regression of the proportion of investment in the PL insurance industry on the underwriting risk. The dependent variable is the proportion of common stock portfolio in the PL insurance industry. The other variables are defined in Table 6. The regression models are Tobit and Heckman. For the Tobit model, the left-censoring limit is 0, the right-censoring limit is 1, and random effects are included. For the Heckman model, firm fixed effects are included in the second stage. The standard errors (in parentheses) are clustered at the insurer level. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Table 9
Effects of Underwriting Risk on Industry Bias in the PL Insurance Industry

Dependent Variable: Industry Bias in PL Insurance Industry (IB)		
Model:	Tobit	Heckman
INTERCEPT	-17.4515***	-12.9273
	(2.2819)	(9.0564)
UND_RISK	-0.6563**	-0.8983***
	(0.3116)	(0.2976)
AGE	0.0260	0.4721
	(0.2291)	(0.7316)
SIZE	0.6897***	0.8218
	(0.2260)	(0.6080)
NPW_SIZE	-0.0017	-0.1703
	(0.1758)	(0.3442)
PUBLIC	-0.0628	1.3522**
	(0.7747)	(0.5944)
PTF_MV	-0.2515***	-0.7977***
	(0.0940)	(0.3069)
PTF_DIV	1.2930***	0.9984**
	(0.1092)	(0.3994)
MUTUAL	-0.3164	-1.5101**
	(0.4157)	(0.6583)
REINSURANCE	-1.4012**	-1.3715
	(0.6250)	(1.2397)
LONG_TAIL	0.2419	0.5273
	(0.6260)	(1.2572)
LINES_DIV	-1.6859**	0.3438
	(0.8428)	(1.2262)
GEO_DIV	0.2075	0.4203
	(0.7069)	(1.2347)
Lambda		0.4203
		(1.2347)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	No	Yes
Line Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
N. of Obs.	5,843	2,094

This table presents the results from the regression of the industry bias on the underwriting risk. The dependent variable is the industry bias. The other variables are defined in Table 6. The regression models are Tobit and Heckman. For the Tobit model, the left-censoring limit is -1, the right-censoring limit is $(1- w_m)/ w_m$, and random effects are included. For the Heckman model, firm fixed effects are included in the second stage. The standard errors (in parentheses) are clustered at the insurer level. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

CONCLUSION

In this study, we investigate the industry bias in PL insurers' common stock portfolios. There are two competing theories in predicting the industry bias. The familiarity-based theory suggests that investors should tilt their portfolios toward industrially close stocks, while the hedging-based theory argues that investors should hedge their non-financial income risk by tilting their portfolios toward the industrially remote stocks. In terms of the familiarity, it can be driven by either asymmetric information or a behavioral bias, and prior studies have found conflicting empirical evidence.

Through empirical analysis, we provide evidence in support of both the familiarity-based theory and the hedging-based theory. Specifically, we find a negative industry bias in PL insurers' common stock portfolios, implying that PL insurers tilt their common stock portfolios away from their industry and toward the other industries. Then we investigate the nature of the industry bias. We show that PL insurers have information advantages in investing in their industrially close stocks, supporting the information-based familiarity. In addition, we find direct evidence in support of the hedging motive. Specifically, the underwriting risk leads PL insurers to tilt their portfolios away from their industrially close stocks. Therefore, we conclude that the PL insurers' negative industry bias is driven by hedging even though they have asymmetric information in their industry.

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ESSAY II

DO INSTITUTIONAL INVESTORS BET AGAINST BETA? EMPIRICAL EVIDENCE FROM THE U.S. PROPERTY-LIABILITY INSURANCE INDUSTRY

INTRODUCTION

A basic tenet of the capital asset pricing model (CAPM) by Sharpe (1964) and Lintner (1965) is that exposure to market risk is compensated by the market risk premium. The model implies that investors invest in the portfolio with the highest expected excess return per unit of risk (Sharpe ratio). However, prior studies have found that the security market line (SML) (i.e., the line relating the expected return on a risky asset to its beta) is too flat relative to the CAPM (e.g., Black, 1972; Black, Jensen, and Scholes, 1972; Friend and Blume, 1970; Black, 1993; Mehrling, 2005). For example, Friend and Blume (1970) and Black, Jensen, and Scholes (1972) demonstrate that the high-beta portfolio produces lower returns than implied by the CAPM and therefore has a negative alpha (i.e., is overpriced), while the low-beta portfolio produces higher returns than implied by the CAPM and therefore has a positive alpha (i.e., is underpriced), both contributing to the SML flatness. The positive (negative) abnormal returns of low-beta (high-beta) portfolios are referred to as the beta anomaly, which implies that the low-beta portfolio outperforms the high-beta portfolio (e.g., Bali, Brown, Murray, and Tang, 2016)[19].

Based on the beta anomaly found in the prior literature, Frazzini and Pedersen (2014) propose the betting-against-beta (BAB) strategy. BAB refers to the behavior of portfolio tilting toward low-beta assets and applying leverage. Given that the target excess return and the overall risk do not change, leverage must be used to boost the excess return of the low-beta portfolio to

[19] Prior studies also report that the beta anomaly is more pronounced after controlling for size and book-to-market characteristics (Fama and French, 1992; Fama and French, 2006) and during the periods of high inflation (Cohen, Polk, and Voulteenaho, 2005), disagreement about stock market earnings (Hong and Sraer, 2016), and investor sentiment (Antoniou, Doukas, and Subrahmanyam, 2015).

the level of the high-beta portfolio[20]. Utilizing data in multiple financial markets, they confirm the outperformance of the low-beta assets. Thus, they postulate that investors who are less financially constrained should overweight low-beta assets in their portfolios. Consistent with their prediction, they find anecdotal evidence in the real world that Berkshire Hathaway and leveraged buyout (LBO) funds, who use leverage, hold portfolios of a lower beta than retail investors and mutual funds, who are likely to be constrained. However, the BAB strategy is challenged by Cederburg and O'Doherty (2016). They argue that the alphas estimated by prior literature using the unconditional CAPM are downward biased estimates of true alphas. They find evidence that the conditional CAPM can resolve the beta anomaly. Specifically, the differences in conditional alphas across beta portfolios are statistically insignificant. Therefore, Cederburg and O'Doherty (2016) conclude that it does not pay to bet against beta.

However, whether investors in the real world bet against beta has not been formally examined in the prior literature. So, it is still unknown whether investors who use leverage tilt toward low-beta assets in order to earn abnormal returns. If the beta anomaly is purely a product of an estimation bias in the unconditional CAPM, we would expect that investors do not bet

[20] The BAB strategy requires leverage, and the leverage distinguishes the betting against beta from portfolio tilt due to changes in investors' risk appetite. Frazzini and Pedersen (2014) provide an example of Treasuries to illustrate the economic mechanism that could be at work. The following is another similar numerical example. For simplicity, suppose there is no risk-free return (i.e., risk-free rate is zero), interest of borrowing (i.e., interest rate is zero), tax on capital gains (i.e., tax rate is zero), or abnormal returns (i.e., alpha is zero). Also assume that the market return is 1% and its volatility is 1%. If an investor invests $1 in a stock with a beta of 2 then the excess return of this stock can be calculated as 2×1%=2%. Since the abnormal return is assumed to be zero, the total return will also be 2%. The volatility of the stock returns is equal to the product of the volatility of the market returns and the stock beta (i.e., 1%×2=2%). If this investor rather chooses to invest the $1 in a stock with a beta of 1 then the excess return is 1×1%=1%, the total return is 1%, and the return volatility is 1% (i.e., 1%×1=1%). In the latter case, the investor holds a stock that has a lower risk and a lower return, but the Sharpe ratio remains the same (i.e., both are 1). However, if this investor borrows another $1 and invests his $2 in the stock with a beta of 1, the investor will obtain a portfolio that has an excess return of 2%, a total return of 2%, and a volatility of 2%. Correspondingly, the portfolio beta becomes 2. Thus, in this case with borrowing, the excess return, total return, volatility, and Sharpe ratio are the identical to those in the case when the investor invests just $1 in a stock with a beta of 2 without borrowing. Frazzini and Pedersen (2014) suggest that the incentive for the investor to borrow money and switch to low-beta stocks, albeit the portfolio beta is unchanged, is to pursue low-beta stocks' higher abnormal returns (i.e., alpha), which we assume to be 0 in this example. Therefore, leverage is indispensable in the BAB strategy, and the simple portfolio tilt toward low-beta stocks without applying leverage is not betting against beta and may reflect just changes in investors' risk appetite.

against beta and the negative leverage-beta relation found by Frazzini and Pedersen (2014) from the anecdotal evidence does not hold. In this study, we investigate the common stock portfolios of the U.S. property-liability (PL) insurers and attempt to bridge this gap.

An important advantage of studying PL insurers is that we can directly observe their leverage. Frazzini and Pedersen (2014) use Berkshire Hathaway as an example of the investor who uses leverage and examine whether it bets against beta. They report that Berkshire Hathaway employs leverage via insurance float and issuing debt. In our study, PL insurers apply leverage in the same way. They collect premiums upfront and pay claims later, and the collected premiums that have not been paid out in claims are referred to as insurance float[21]. PL insurers invest the float to earn investment income until claims are paid out, and thus, the float is an important component of PL insurers' leverage in their investing. In the literature, the leverage funded by the float is named insurance leverage (Xie, Wang, Zhao, and Lu, 2017). Besides the insurance leverage, PL insurers also utilize debt financing via both long-term and short-term debt issuances[22]. According to a special report by A.M. Best (2017), the aggregate debt-to-capital ratio of publicly traded PL insurers is 50 percent at the beginning of 2009. Even though the ratio declines to 25 percent at the end of 2012 due to the 2008 financial crisis, it has maintained within the range between 22 percent to 25 percent since the beginning of 2013. In the literature, this leverage is named financial debt leverage (Xie et al., 2017). In our study, we follow Frazzini and Pedersen (2014) and use the total firm leverage as a comprehensive measure of leverage that

[21] To be more specific, "the major components of float are unpaid losses, life, annuity and health benefit liabilities, unearned premiums and other liabilities to policyholders less premium and reinsurance receivables, deferred charges assumed under retroactive reinsurance contracts and deferred policy acquisition costs (Berkshire Hathaway, 2016)."
[22] To be more specific, the financial debt of PL insurers consists of borrowed money and interest thereon, amount withheld or retained for account of others, adjustment in liabilities due to exchange rates, drafts outstanding, payable to parent, subs and affiliates, derivatives, payable for securities and payable for securities lending (Xie et al., 2017).

reflects both PL insurers' insurance leverage and their financial debt leverage[23]. The statutory statements of PL insurers contain all the data needed to calculate this measure and make it viable to examine the investors' leverage. By contrast, we do not choose to study some other investors (e.g., individual investors and hedge funds[24]) because it is difficult to observe their leverage without access to proprietary data.

Through empirical analysis, we find that the PL insurers' portfolio beta choice is not negatively related to their leverage, implying that they do not bet against beta. We also explore the explanation by testing the performance of their low-beta holdings and high-beta holdings. Using a holdings-based calendar-time portfolio approach, we find that the differences in neither unconditional alphas nor conditional alphas across the beta portfolios are statistically significant, suggesting that the low-beta portfolio does not outperform the high-beta portfolio. Taken together, our study suggests that the BAB does not exist.

The remainder of this paper is organized as follows. The "Literature Review" provides a summary of the prior literature. The "Hypotheses Development" section proposes the hypotheses that we test in this study. Next, the "Empirical Method" section presents the methods used in our empirical analysis. Then, the "Data and Sample" section describes the data and sample used in our analysis. The "Portfolio Tilt Regarding Beta" section reports the results from the examining the portfolio tilt toward various levels of beta. The "Beta-Leverage Relation" section reports the results from the analyzing the effects of leverage on the portfolio beta choice. The "Performance of the BAB Strategy" section presents the results from comparing the performance of the low-beta portfolio and the performance of the high-beta portfolio. Last, the "Conclusion" section concludes our study.

[23] We also reproduce the results in our analysis using the insurance leverage and the financial debt leverage individually, and the results are qualitatively the same.
[24] See Ang, Gorovyy, and Van Inwegen (2011).

LITERATURE REVIEW

Prior studies widely document a beta anomaly in stock returns (e.g., Black, 1972; Black, Jensen, and Scholes, 1972; Friend and Blume, 1970; Black, 1993; Mehrling, 2005). For example, Friend and Blume (1970) and Black, Jensen, and Scholes (1972) find that portfolios of high-beta (low-beta) stocks earn lower (higher) returns than predicted by the CAPM model, implying that their alphas are negative (positive). Frazzini and Pedersen (2014) formalize this idea and propose the BAB strategy. They argue that the trading strategy that takes a short position on high-beta assets and a long positive on levered low-beta assets generates superior excess returns and investors who are less financially constrained should overweight low-beta assets. They provide consistent empirical evidence in support of their propositions.

Following Frazzini and Pedersen (2014), many studies find further evidence for the beta anomaly. For example, Asness, Frazzini, and Pedersen (2014) address the concern that the superior return of low-beta stocks might be simply due to the industry bets that favor a slowly changing set of stodgy and stable industries. They examine the benefits of betting against beta using two new BAB factors, the industry-neutral BAB and the BAB as a pure industry bet. Their evidence disproves the notion that BAB is merely an industry bet. They show that betting against beta can generate positive risk-adjusted returns both as an industry-neutral bet within each industry and as a pure bet across industries. They also investigate the performance of the BAB factors net of transaction costs. They find that the performance of the BAB factors remains significant for the regular BAB, the industry-neutral BAB, and the industry BAB.

Many studies also attempt to identify the driver of the beta anomaly. For example, Bali, Brown, Murray, and Tang (2016) investigate the role of a lottery demand factor in explaining expected stock returns. The find that the demand for lottery-like stocks is an important driver of beta anomaly. Specifically, they show that the beta anomaly does not exist when the beta-sorted portfolios are constructed to be neutral to lottery demand and it exists only when the price impact of lottery demand falls disproportionately on high-beta stocks. In addition, they show that the beta anomaly is concentrated in stocks with low levels of institutional ownership. Novy-Marx (2016) investigates the driver of the beta anomaly from the perspective of firm characteristics. He finds that the tilt of high-beta stocks toward small, unprofitable, and growth firms explains the poor absolute performance of the aggressive stocks. Huang, Lou, and Polk (2016) study the response of arbitrageurs to the flatness of the SML and find that the beta arbitrage activities instead produce booms and busts in the strategy's abnormal trading profits. Specifically, the abnormal returns take longer to materialize when the beta arbitrage activity is low, and the price overshoot as the short-run abnormal returns are larger when the beta arbitrage activity is high. They also show a novel positive-feedback channel operating through the firm leverage that facilitates the booms and busts. Malkhozov, Mueller, Vedolin, and Venter (2016) investigate the effects of frictions on asset prices internationally and find that local illiquidity helps explain the variations in the performance of BAB strategies across countries. They show that trading strategies conditional on illiquidity are associated with highly significant alphas and Sharpe ratios. Boguth and Simutin (2016) propose a demand-based measure of the leverage constraints in mutual funds and find that the average market beta of actively managed mutual funds captures the leverage demand and the tightness of leverage constraints and strongly predicts returns of BAB portfolios.

Even though the BAB strategy has been widely documented in the literature, its theoretical basis is severely undermined by Cederburg and O'Doherty (2016). We revisit the BAB strategy proposed by Frazzini and Pedersen (2014) and discuss the argument of Cederburg and O'Doherty (2016) in the following section while developing our hypotheses.

HYPOTHESES DEVELOPMENT

According to Frazzini and Pedersen (2014), the BAB strategy is long leveraged low-beta stocks and short high-beta stocks. Their model implies that the slope of the SML depends on the tightness of funding constraints, which vary across both investors and time. To illustrate the asset pricing effects of funding constraints, they construct a BAB factor, which is a portfolio that holds low-beta assets, leveraged to a beta of one, and that shorts high-beta assets, deleveraged to a beta of one. They predict that the BAB factor earns a positive return and the return is positively related to both the funding constraints and the spread in betas between high-beta and low-beta securities. In addition, their model implies that the market must be segmented on beta. Specifically, given that BAB is profitable and leverage is required in this investment strategy, they argue that the investors who are more-constrained should overweight high-beta assets in their portfolios, while less-constrained investors should overweight low-beta assets in their portfolios by applying leverage.

Frazzini and Pedersen (2014) empirically test their BAB strategy by studying a sample of U.S. and international securities. They find that the high-beta portfolio has a lower alpha and a lower Sharpe ratio than the low-beta portfolio and the SML flatness is a common issue on not only U.S. equity markets but also international equity markets, Treasury markets, and future markets. Therefore, investors should have an incentive to apply leverage and tilt their portfolios toward low-beta stocks. Even though Frazzini and Pedersen (2014) do not formally test this proposition, they examine the portfolios held by several classes of investors and provide consistent anecdotal evidence. Specifically, they show that Berkshire Hathaway and leveraged buyout (LBO) funds, who use leverage, hold portfolios with a beta that is significantly below one. By contrast, mutual funds and retail investors, who are likely to be constrained, hold portfolios with a beta that is significantly above one. Their study implies that the portfolio beta is negatively related to the investors' leverage. Similar to Berkshire Hathaway, PL insurers invest in common stocks and apply leverage via insurance float and issuing debt. If the BAB strategy holds, their low-beta portfolio should outperform their high-beta portfolio, and the higher PL insurers' leverage, the more capital they should allocate to low-beta stocks in order to obtain a higher alpha.

However, the BAB strategy is challenged by Cederburg and O'Doherty (2016). Their argument is based on the prior literature on the bias of unconditional alphas. Many studies report that unconditional alphas are biased estimates of true alphas if betas vary with the market risk premium or market volatility (e.g., Grant, 1977; Jagannathan and Wang, 1996; Lewellen and Nagel, 2006; Boguth, Carlson, Fisher, and Simutin, 2011). Cederburg and O'Doherty (2016) analyze the systematic trends of the portfolio beta for the high-minus-low beta portfolio, the market excess return, and the market volatility. They show that the beta is negatively related to the expected excess return on the market and positively related to market volatility, both contributing to a negative bias in unconditional alphas. Therefore, they reconsider the evidence of the beta anomaly and investigate the abnormal returns of the BAB strategy. They find that in comparison to the unconditional case, the differences in conditional alphas across beta portfolios are substantially smaller in economic magnitude and statistically insignificant. In other words, low-beta stocks do not outperform high-beta stocks, implying that betting against beta does not pay. Their study suggests that the conditional CAPM successfully resolves the beta anomaly.

Therefore, investors should not have an incentive to apply leverage and bet against beta. In other words, leverage is not a determinant of investors' portfolio beta choice.

In our setting, if the unconditional alphas are biased estimates of the true alphas and the BAB strategy does not hold, we would expect that the PL insurers' low-beta portfolio does not outperform their high-beta portfolio. Therefore, they should not have any incentive to bet against beta. So, the relation between PL insurers' portfolio beta and their leverage is not supposed to be negative or significant. Taken together, the above discussion leads to the following competing hypotheses,

H1 (Beta-Leverage Relation): *PL insurers' portfolio beta is negatively related to their leverage.*

H2 (Beta-Leverage Relation): *PL insurers' portfolio beta is not negatively related to their leverage.*

EMPIRICAL METHODS

Measure of Portfolio Tilt Regarding Beta

Before testing our hypotheses, we first investigate PL insurers' beta choice in their common stock portfolios. The reporting requirements in the U.S. PL insurance industry allow us to observe PL insurers' common stock holdings at the end of each year. Using their year-end actual holding data, we examine whether they tilt their portfolios toward stocks with certain betas (i.e., high or low betas). To measure this portfolio tilt, we employ the portfolio bias that is commonly used in the literature (e.g., Van Nieuwerburgh and Veldkamp, 2009; Seasholes and Zhu, 2010; Døskeland and Hvide, 2011). We name the portfolio bias toward different stock betas "beta bias (BB)".

Following Seasholes and Zhu (2010) and Døskeland and Hvide (2011), we employ the market portfolio as the benchmark and use the beta deciles of the stocks in the market portfolio as the break points. Consistent with Seasholes and Zhu (2010), our beta bias is measured by the excess weight of the stocks in investors' portfolios over their market weight scaled by the market weight in each beta decile. This measure is calculated as follows,

$$BB = \frac{w_p - w_m}{w_m} \tag{1}$$

where w_p represents the percentage of a PL insurer's portfolio in a beta decile and w_m represents the percentage of the market portfolio in this decile.

Unconditional CAPM

The Sharpe-Linter CAPM theory builds on the mean-variance-efficiency model developed by Markowitz (1959). It assumes that (1) all investors are risk averse, (2) all investors have the same decision horizons, (3) the capital markets are perfect, and (4) all investors have homogenous expectations and portfolio opportunities (e.g., Sharpe, 1964; Lintner, 1965; Jensen, 1968; Fama, 1968). The Sharpe-Linter CAPM implies that the expected return on any asset is equal to the risk-free interest rate plus the market risk premium, which is the product of the premium per unit of beta risk and the asset's market beta. The equation is as follows,

$$E(r_i) = r_f + \left[E(r_m) - r_f\right]\beta_i \tag{4}$$

where r_i represents the return on asset i, r_f represents the risk-free interest rate, r_M represents the market return, and β_i represents the asset's market beta. Jensen (1968) allows for the existence of a non-zero constant in the time series regression test. The estimating equation can be written as follows,

$$R_{i,t} = \alpha_i + R_{m,t}\beta_i + \mu_{i,t} \tag{5}$$

where $R_{i,t}$ represents the excess return for asset i during period t (i.e., $r_{i,t} - r_{f,t}$), $R_{m,t}$ represents the excess return of the market portfolio during period t (i.e., $r_{m,t} - r_{f,t}$), β_i represents the asset i's market beta, and α_i represents the intercept ("Jensen's alpha"). The equation (5) is widely used as the unconditional CAPM in the literature.

Following Frazzini and Pedersen (2014), we estimate unconditional betas from rolling regressions of excess returns on market excess returns using daily data. The estimated time series beta for security i is given by,

$$\hat{\beta}_i^{ts} = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m} \tag{6}$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the excess stock returns and the excess market returns, respectively, and $\hat{\rho}$ represents their correlation. Consistent with Frazzini and Pedersen (2014), we use one-year rolling standard deviation for volatilities and a five-year horizon for the correlation to account for the fact that correlations move more slowly than volatilities. In addition, we require at least six months (120 trading days) of non-missing data to estimate volatilities and at least three years (750 trading days) of non-missing data to estimate correlations. Following Vasicek (1973) and Elton, Gruber, Brown, and Goetzmann (2003), we shrink the time series estimate of beta ($\hat{\beta}_i^{ts}$) toward the cross-sectional mean ($\hat{\beta}_i^{xs}$) as follows,

$$\hat{\beta}_i = w_i \hat{\beta}_i^{ts} + (1 - w_i)\hat{\beta}_i^{xs} \tag{7}$$

where w_i represents the shrinkage factor. Consistent with Frazzini and Pedersen (2014), we set $w_i = 0.6$ and $\hat{\beta}_i^{xs} = 1$ for all stocks in all periods.

Conditional CAPM

The unconditional tests mentioned in the previous section restrict α_i and β_i in Equation (5) to be constant. By contrast, the conditional tests model betas as a function of a set of state variables (i.e., instruments) (Lewellen and Nagel, 2006). According to Cederburg and O'Doherty (2016), the conditional CAPM implies that:

$$\alpha_{i,t} \equiv E\left(R_{i,t} \middle| I_{t-1}\right) - \beta_{i,t} E\left(R_{m,t} \middle| I_{t-1}\right) = 0 \tag{8}$$

where $R_{i,t}$ represents portfolio i's excess return during period t, $R_{m,t}$ represents the excess return of the market portfolio during period t, I_{t-1} represents the investor information set at the end of period $t - 1$, and $\beta_{i,t}$ represents the conditional beta of portfolio i. Correspondingly, $\beta_{i,t}$ is given by:

$$\beta_{i,t} = \frac{Cov\left(R_{i,t}, R_{m,t} \middle| I_{t-1}\right)}{Var\left(R_{m,t} \middle| I_{t-1}\right)} \tag{9}$$

A common approach in the literature is to use observed macroeconomic variables such as the dividend yield and default spread as the state variables (e.g., Shanken, 1990; Ferson and Schadt, 1996, Ferson and Harvey, 1999). Boguth et al. (2011) also show that introducing lagged realized betas into instrument variables (IV) estimators is effective to correct market- and volatility-timing biases[25] without overconditioning.

We follow Cederburg and O'Doherty (2016) and use both the one-step IV (IV1) and the two-step IV model (IV2) to examine the performance of PL insurers' low-beta portfolio and high-beta portfolio. The regression model is as follows,

$$R_{i,\tau} = \alpha_i^{IV1} + \left(\gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1}\right) R_{m,\tau} + u_{i,\tau} \tag{10}$$

where $R_{i,\tau}$ represents the quarterly buy-and-hold excess return for portfolio i over quarter τ, $R_{m,\tau}$ represents the quarterly buy-and-hold excess return for the market portfolio over quarter τ, and $Z_{i,\tau-1}$ represents a $k \times 1$ vector of instruments for portfolio i over quarter τ. Fama and French (1992 and 2006) show that the risk-return relation becomes even flatter after controlling for both size and book-to-market. Therefore, we follow Cederburg and O'Doherty (2016) and investigate the portfolio performance in the Fama-French three-factor model. Since the conditional CAPM model is based on quarterly portfolio returns, we construct a quarterly version of the Fama-French size and value factor ($R_{smb,\tau}$, and $R_{hml,\tau}$) by compounding the monthly returns for the long and short sides of each factor. The IV1 regression based on the Fama-French model is as follows,

$$R_{i,\tau} = \alpha_i^{IV1} + \left(\lambda_{i,0} + \lambda_{i,1}' Z_{i,\tau-1}^{\lambda}\right) R_{m,\tau} + \left(\theta_{i,0} + \theta_{i,1}' Z_{i,\tau-1}^{\theta}\right) R_{smb,\tau}$$

[25] As is mentioned in the Section 3 (Hypotheses Development), unconditional alphas are biased estimates of true alphas if betas vary with the market risk premium or market volatility (e.g., Grant, 1977; Jagannathan and Wang, 1996; Lewellen and Nagel, 2006; Boguth et al., 2011).

$$+\left(\eta_{i,0} + \eta'_{i,1} Z^{\eta}_{i,\tau-1}\right) R_{hml,\tau} + \mu_{i,\tau} \tag{11}$$

To estimate the two-step IV model, we first use daily portfolio return data to estimate a separate CAPM regression for each quarter τ and get a time series of nonoverlapping conditional CAPM regression parameters. The regression model is given by,

$$r_{i,j} = \alpha_i + \beta_{i,0} r_{m,j} + \beta_{i,1} r_{m,j-1} + \beta_{i,2}\left[\frac{r_{m,j-2} + r_{m,j-3} + r_{m,j-4}}{3}\right] + \varepsilon_{i,j} \tag{12}$$

where $r_{i,j}$ represents the excess return for a given portfolio i on day j of quarter τ and $r_{m,j}$ represents the excess market return on day j of quarter τ. The portfolio beta estimate for quarter τ is as follows,

$$\hat{\beta}_{i,\tau} \equiv \hat{\beta}_{i,0} + \hat{\beta}_{i,1} + \hat{\beta}_{i,2} \tag{13}$$

The first stage model is as follows,

$$\hat{\beta}_{i,\tau} = \delta_{i,0} + \delta'_{i,1} Z_{i,\tau-1} + e_{i,\tau} \tag{14}$$

where $\hat{\beta}_{i,\tau}$ represents the estimated quarterly portfolio beta and $Z_{i,\tau-1}$ represents a $k \times 1$ vector of instruments for a given portfolio. The second stage model is as follows,

$$R_{i,\tau} = \alpha_i^{IV2} + \left(\phi_{i,0} + \phi_{i,1}\tilde{\beta}_{i,\tau}\right) R_{m,\tau} + v_{i,\tau} \tag{15}$$

where $R_{i,\tau}$ represents the quarterly buy-and-hold excess return for portfolio i over quarter τ and $R_{m,\tau}$ represents the quarterly buy-and-hold excess return for the market portfolio.

The instruments $Z_{i,\tau-1}$ are needed in both the one-step and the two-step IV model. Following Cederburg and O'Doherty (2016), we include the common macroeconomic state variables (i.e., dividend yield[26] and default spread[27]) and lagged short-term and long-term betas in the set of conditioning information. For the lagged short-term and long-term betas, we use

[26] Following Cederburg and O'Doherty (2016), the dividend yield is calculated as the log of the sum of dividends accruing to the CRSP value-weighted market portfolio over the prior 12 months minus the log of the lagged index level.

[27] Following Cederburg and O'Doherty (2016), the default spread is calculated as the yield spread between Moody's Baa- and Aaa-rated bonds.

lagged three-month and 36-month beta (β^{LC3} and β^{LC36}) measures (i.e., lagged-component betas). The lagged-component (LC) beta for a given portfolio at the end of quarter $\tau - 1$ is estimated as the portfolio-weighted average of lagged beta estimates for constituent firms to be included in the portfolio in quarter τ. Following the advice of Cederburg and O'Doherty (2016), we avoid using any firm return data that overlap with the data used to estimate the portfolio formation-period betas. As is discussed later, in our examination of the performance of the low-beta portfolio and high-beta portfolio, the formation-period betas are estimated using 12 months of the CRSP daily return data and rebalanced at the beginning of each July. Consistent with Cederburg and O'Doherty (2016), the short-term lagged-component beta (β^{LC3}) is estimated using daily return data within a lagged three-month period. The regression models are given by equations (12) and (13). Particularly, during the third quarter in a year, we use firm betas from the second quarter in the prior year because the second quarter in the contemporaneous year falls within the period that is used to estimate the formation-period betas. For the first, second, and fourth quarters in a year, we estimate β^{LC3} from the immediate preceding quarter. Cederburg and O'Doherty (2016) argue that the predictivity of β^{LC3} might be diminished during the third quarter. Therefore, our instruments also incorporate a dummy variable that serves as the third-quarter indicator ($I_{\{Q3\}}$) and an interaction term between the indicator and the short-term lagged-component beta ($I_{\{Q3\}} \times \beta^{LC3}$) to allow for a differential effect. In terms of the long-term lagged-component beta (β^{LC36}), we use the daily return data over the 36-month period immediately preceding the formation period. Following Cederburg and O'Doherty (2016), we require at least 36 and 450 valid return observations during the three-month and 36-month period to estimate the β^{LC3} and β^{LC36}, respectively.

Holdings-Based Calendar-Time Portfolios

To examine the performance of PL insurers' low-beta portfolio and high-beta portfolio, we follow Seasholes and Zhu (2010) and construct holdings-based calendar-time portfolios using PL insurers' stock holding data. The advantage of the holdings-based calendar-time portfolios is that they reflect the actual weight of each stock in PL insurers' holdings. To construct the calendar-time portfolios, we first sort PL insurers' holdings into decile portfolios based on past market betas using all listed firms for the break points. Consistent with Cederburg and O'Doherty (2016), the formation-period betas are estimated from the prior 12 months (240 trading days) of the CRSP daily return data following equations (12) and (13). The portfolios are rebalanced at the beginning of each July.[28] To be included in the break points formation, a firm must have at least 150 valid daily return observations over the prior 12 months (240 trading days). Following Seasholes and Zhu (2010), when the portfolios are rebalanced, the weights of each stock in the decile portfolios are determined by its actual value in the PL insurers' holdings at the beginning of the rebalancing date. Consistent with Frazzini and Pedersen (2014) and Cederburg and O'Doherty (2016), we regard the first decile portfolio as the low-beta portfolio and the last decile portfolio as the high-beta portfolio. Consistent with Cederburg and O'Doherty (2016), the PL insurers' beta decile portfolios are assumed to be held for 12 months before

[28] Since the statutory statements of PL insurers provide their stock holdings at the year-end only, the stock holdings at the beginning of July are not directly observed. With the assistance of daily transactions data, we convert the year-end holdings to holdings on each trading day. To complete this conversion, the first step is to get adjusted number of shares of each stock in PL insurers' portfolios. Specifically, after we obtain the data of annual stock holdings and stock transactions (discussed in the Data and Sample section), we use the cumulative factor (CFACSHR) provided by the CRSP daily stock file to adjust the number of shares held and transacted. The second step is to use a retrospective method to get the adjusted number of shares held on each trading day during a year. For example, if Allstate holds 1,000 shares of Chubb at the end of 2016 and the only transaction it makes during this year is on March 12, 2015, when it buys 500 shares. The retrospective method will assign 1,000 to the number of shares on each trading day between March 12, 2015 and December 31, 2015 and assign 500 (i.e., 1,000 − 500) to the number of shares on each trading day between January 1, 2015 and March 11, 2015. The last step is to determine the market value of stock holdings in each stock using the price that is also adjusted by a cumulative factor (CFACPR) provided by the CRSP daily stock file. With PL insurers' daily holdings data, we can obtain their actual holdings at the beginning of July in each year.

rebalancing. To calculate the daily returns of each portfolios, we follow Liu and Strong (2008) and employ the decomposed buy-and-hold methods[29] rather than rebalanced methods to ensure that the returns correspond to those realized by a buy-and-hold investor.

Investigation of the Beta-Leverage Relation

To test H1 and H2, we conduct multivariate regressions of PL insurers' beta choice on their leverage. Since the firm characteristics are observed at the year-end, we choose the year-end portfolios in testing the role of leverage in determining the beta choice. Consistent with our prior analysis, both the unconditional and conditional CAPM are used to estimate the stock beta. For the multivariate regressions, we employ three different approaches.

The first approach uses the value-weighted unconditional and conditional portfolio beta (UN_PTF_BETA and CO_PTF_BETA) as the dependent variable. The model is given by

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[29] Specifically, the daily portfolio return over *n*-day holding period is given as follows,

$$r_{p,t} = \begin{cases} \sum_{i=1}^{N} w_{i,0} r_{i,t}\,, & t = 1 \\ \sum_{i=1}^{N} \frac{w_{i,0} \prod_{d=1}^{t-1}(1 + r_{i,d})}{\sum_{j=1}^{N}[w_{j,0} \prod_{d=1}^{t-1}(1 + r_{i,d})]} r_{it}\,, & t = 2, \dots, n \end{cases}$$

where $r_{p,t}$ represents the portfolio return on day t, $w_{i,0}$ represents the weight of stock i at the beginning of the holding period and $r_{i,t}$ ($r_{i,d}$) represents the return of stock i on day t (d). Since we construct value-weighted portfolios, $w_{i,0}$ can begiven by

$$w_{i,0} = \frac{MV_{i,0}}{\sum_{j=1}^{N} MV_{j,0}}$$

where $MV_{i,0}$ is the market value of stock i at the beginning of the holding period. When we compare the performance of PL insurers' low-beta portfolio and their high-beta portfolio, we form a long-short portfolio that is long high-beta stocks and short low-beta stocks. Consistent with Liu and Strong (2008), the profits of the long-short portfolio are calculated as follows,

$$AP_t = \begin{cases} r_{L,t} - r_{S,t}, & t = 1 \\ r_{L,t} \prod_{d=1}^{t-1}(1 + r_{L,d}) - r_{S,t} \prod_{d=1}^{t-1}(1 + r_{S,d}), & t = 2, \dots, n \end{cases}$$

where AP_t represents the profits of the long-short portfolio on day t and $r_{L,t}$ and $r_{S,t}$ ($r_{L,d}$ and $r_{S,d}$) represents the long and the short portfolio return on day t (d), respectively.

$$UN\_PTF\_BETA, \text{ or } CO\_PTF\_BETA = f(LEV, Controls) \quad (14)$$

where UN_PTF_BETA and UN_PTF_BETA represent the unconditional portfolio beta and conditional portfolio beta, respectively, and LEV represents the leverage. As is discussed in the Section 1 (Introduction), we use the firm total leverage which reflects both the insurance leverage and financial debt leverage. Following the prior literature, LEV is calculated as the ratio of total liabilities to total assets (e.g., Colquitt, Sommer, and Godwin, 1999). The regression model is the ordinary least squares (OLS).

The second approach uses the proportion of investment in an unconditional and conditional beta decile ($UN\_PRO\_D(1,2,\dots,10)$ and $CO\_PRO\_D(1,2,\dots,10)$) as the dependent variable. The model is given by

$$UN\_PRO\_D(1,2,\dots,10), \text{ or } CO\_PRO\_D(1,2,\dots,10) = f(LEV, Controls) \quad (17)$$

where $UN\_PRO\_D(1,2,\dots,10)$ ($CO\_PRO\_D(1,2,\dots,10)$) represents the proportions of the common stock portfolio in stocks with an unconditonal (conditional) beta in the deciles 1, 2, …, 10, respectively. We employ the Tobit regression model because the values for the proportions are bounded between 0 and 1. The likelihood-ratio test suggests that the random-effect model is preferable to the pooled model. Thus, the model used in the second approach is the Tobit with the random effects.

The third approach uses the beta bias in each unconditional and conditional beta decile ($UN\_BB\_D(1,2,\dots,10)$ and $CO\_BB\_D(1,2,\dots,10)$) as the dependent variable. Compared to the second approach, the advantage of this approach is that it removes the effects of the market because the market portfolio is used as the benchmark in the calculation of the beta bias. The models are given by

$$UN\_BB\_D(1,2,\dots,10), \text{ or } CO\_BB\_D(1,2,\dots,10) = f(LEV, Controls) \quad (18)$$

where $UN\_BB\_D(1, 2, \ldots, 10)$ ($CO\_BB\_D(1, 2, \ldots, 10)$) represents the beta bias (measured by BB) in stocks with an unconditional (conditional) beta in the deciles 1, 2, …, 10, respectively. Since the beta bias measures are all bounded, we use the Tobit model. The left-censoring limit is -1, and the right-censoring limit $(1- w_m)/w_m$, where w_m represents the percentage of the market portfolio in a beta decile. Again, the likelihood-ratio test favors the random-effect model. So, we employ the Tobit regression model with random effects.

In the finance literature, few studies propose or examine the firm characteristics of institutional investors in determining the common stock portfolio constitution. Prior research in the portfolio choice (e.g., Massa, Simonov, 2006; Døskeland and Hvide, 2011; Keloharju, Knüpfer, and Linnainmaa, 2012) is focused on individual investors because it can observe the individuals' investments and their wealth, income, and demographic characteristics at the same time. Therefore, we apply the available controls from the literature on individual investors in our multivariate regression analysis. Consistent with Døskeland and Hvide (2011), we control for industry experience, gross wealth, income, listing status of the investor's company, market value of the stock portfolio, and portfolio diversification. For PL insurers, the industry experience is measured by the firm age (AGE), which is calculated as natural logarithm of the number of years since commencement. The gross wealth is measured by the firm size ($SIZE$), which is calculated as the natural logarithm of total net admitted assets. The income is measured by the size of net premiums written (NPW_SIZE), which is calculated as the natural logarithm of total net premiums written. The listing status is measured by a dummy variable ($PUBLIC$) that is equal to 1 for a public insurer and 0 for a private insurer. The market value of common stock portfolio (PTF_MV) is measured by the natural logarithm of total market value of common stock holdings. Portfolio diversification (PTF_DIV) is measured by the natural logarithm of the number of stocks held by the insurer. Døskeland and Hvide (2011) also control for the number of stocks in each class on the market. Because we the use the deciles to classify the stocks on the market and number of stocks should be approximately the same across ten beta classes, this variable is equivalent to the year fixed effects. Therefore, we include the year fixed effects in our regression to control for the number of stocks and the other unidentified market characteristics.

In the insurance literature, Ho, Lai, and Lee (2013) study and provide several factors that can explain PL insurers' investment risk taking. Consistent Ho, Lai, and Lee (2013), we incorporate the organization form, reinsurance usage, long-tail insurance, business line diversification, and geographic diversification into the set of control variables. Specifically, the organization form is measured by a dummy variable ($MUTUAL$) which is equal to 1 if the insurer is a mutual insurer and 0 if the insurer is a stock insurer. Reinsurance usage ($REINSURANCE$) is measured by the ratio of premiums ceded to the sum of direct premiums written and reinsurance assumed. The weight of long-tail insurance ($LONG\_TAIL$) is the percentage of net premiums written on long-tail lines[30]. Consistent with Berry-Stölzle, Liebenberg, Ruhland, and Sommer (2012), we measure the business line diversification ($LINES\_DIV$) by the complement of the Herfindahl Index of net premiums written (NPW) across 24 lines of business[31]. The equation is as follows,

$$LINES\_DIV_{i,t} = 1 - \sum_{j=1}^{24} \left(\frac{NPW_{i,j,t}}{NPW_t}\right)^2 \tag{19}$$

[30] Following Phillips, Cummins, and Allen (1998), long-tail lines consist of: Ocean Marine, Medical Professional Liability, International, Reinsurance, Workers' Compensation, Other Liability, Product Liability, Aircraft, Boiler and Machinery, Farmowners Multiple Peril, Homeowners Multiple Peril, Commercial Multiple Peril, and Automobile Liability. Short-tail lines include the following: Inland Marine, Financial Guaranty, Earthquake, Fidelity, Surety, Burglary and Theft, Credit, Fire and Allied Lines, Mortgage Guaranty, and Automobile Physical Damage.

[31] Following Berry-Stölzle et al. (2012), we group similar business lines into 24 distinct lines written by PL insurers: Accident and Health, Aircraft, Auto, Boiler and Machinery, Burglary and Theft, Commercial Multiple Peril, Credit, Earthquake, Farmowners' Multiple Peril, Financial Guaranty, Fidelity, Fire and Allied lines, Homeowners' Multiple Peril, Inland Marine, International, Medical Professional Liability, Mortgage Guaranty, Ocean Marine, Other, Other Liability, Products Liability, Reinsurance, Surety, and Workers' Compensation.

where $NPW_{i,j,t}$ denotes the net premiums written by insurer i in line $j = 1, \ldots, 24$ in year t, and $NPW_{i,t}$ denotes the total net premiums written by insurer i in year t. Larger values of $LINES\_DIV_{i,t}$ represent higher levels of diversification. Consistent with Liebenberg and Sommer (2008), the geographic diversification measure (GEO_DIV) is measured by the complement of the Herfindahl Index of direct premiums written (DPW) across 58 states and territories[32]. The equation is as follows,

$$GEO\_DIV_{i,t} = 1 - \sum_{k=1}^{58} \left(\frac{DPW_{i,k,t}}{DPW_{i,t}} \right)^2 \quad (20)$$

where $DPW_{i,k,t}$ denotes the direct premiums written by an insurer i in state $k = 1, \ldots, 58$ in year t, and $DPW_{i,t}$ denotes the total direct premiums written in year t. In addition, because the U.S. insurance industry is subject to the state regulations rather than the federal regulations, we also include the state fixed effects to control for the potential regulatory effects.

[32] The premiums written across states and territories are obtained from Schedule T of the PL insurers' statutory statements.

DATA AND SAMPLE

We obtain the common stock holdings and transactions (i.e., buys and sells) data of PL insurers from the NAIC InfoPro database for the years 2001 through 2015. The data cover the common stocks of unaffiliated firms[33] on Schedule D – Part 2 – Section 2 (Common Stocks Owned), Part 3 (Long-Term Bonds and Stocks Acquired), Part 4 (Long-Term Bonds and Stocks Sold, Redeemed or Otherwise Disposed Of), and Part 5 (Long Term Bonds and Stocks Acquired and Fully Disposed Of) of PL insurers' annual statutory statements. In our data screen, we first delete stock holdings with nonpositive number of shares or fair value and then aggregate the data for the same stock on each portfolio date (i.e., year-end) or transaction date. The stock information is obtained from the CRSP database. In the last step of data screen, we remove the stock holdings that cannot be merged with the CRSP on the last trading day of each year and stock transactions that cannot be merged with the CRSP on each transaction date. The detailed process of the data screening and the number of observations left following each step are presented in panels A, B, and C of Table 1. Our stock holdings sample consists of 966,986 insurer-stock-year observations, our stock buys sample consists of 980,179 insurer-stock-day observations, and our stock sells sample consists of 907,963 insurer-stock-day observations. The summary statistics are reported in Table 2. On average, the PL insurers in our sample hold 3,391 stocks with 3.04 billion shares and $133.83 billion market value in each year. In terms of stock buys, the PL insurers, on average, buy 0.91 billion shares for $33.11 billion in each year. In

[33] The investments in the common stocks of affiliated companies are excluded in our sample because they might reflect repurchased shares kept as treasury stock that is available for re-issuance rather than investments.

terms of stock sells, the PL insurers, on average, sell 0.87 billion shares for $27.45 billion in each year.

To analyze the effects of leverage on the portfolio beta in the multivariate regressions, we also obtain the financial data of PL insurers from the NAIC InfoPro database. Following prior literature (e.g., Che and Liebenberg, 2017), we exclude insurers with non-positive total net admitted assets, net premiums written, or an organization form other than stock or mutual. Since our study focuses on the common stock portfolios of PL insurers, we also exclude insurers with non-positive market value of common stock portfolios. Finally, we remove the insurers that do not have sufficient information to calculate the variables in the regression analysis. The process of the data screening and the number of observations left following each step are presented in Panel D of Table 1. We winsorize leverage (LEV) and reinsurance ($REINSURANCE$) at the 1st and the 99th percentile to reduce the effects of outliers[34]. Our sample consists of 6,103 insurer-year observations (818 unique insurers), and, on average, it represents 48.48 (56.47) percent of the entire PL industry in terms of total net admitted assets (net premiums written) across all years during our sample period.

In addition, we obtain the risk-free rate, market return, size and value factor from Kenneth French's website[35]. The data of bond yields for the calculation of the default spread are obtained from the Federal Reserve Bank of St. Louis website[36].

[34] We detect outliers using a scatter plot and the Cook's distance test. Both suggest that there are outliers present in the values of our leverage and reinsurance variable.
[35] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[36] See https://fred.stlouisfed.org/.

Table 1
Data Screen

	Screen Criteria	Number of Observations
Panel A: Stock Holdings		
(i)	Obtain PL insurers' stock holdings (unaffiliated) from the NAIC InfoPro database (Schedule D-Part 2-Section 2) (2001-2015).	1,292,954
(ii)	Remove stock holdings with non-positive number of shares or fair value.	1,279,602
(iii)	Aggregate holdings of the same stocks on each portfolio date (year-end) for each PL insurer.	1,184,395
(iv)	Remove stock holdings that cannot be merged with the CRSP database (last trading day in each year).	966,986
Panel B: Stock Buys		
(i)	Obtain PL insurers' stock buys (unaffiliated) from the NAIC InfoPro database (Schedule D-Part 3 and Part 5) (2001-2015).	1,394,770
(ii)	Remove stock buys with non-positive number of shares or actual costs.	1,351,234
(iii)	Aggregate buys of the same stocks on each transaction date for each PL insurer.	1,229,701
(iv)	Remove stocks buys that cannot be merged with the CRSP database on each transaction date.	980,179
Panel C: Stock Sells		
(i)	Obtain PL insurers' stock sells (unaffiliated) from the NAIC InfoPro database (Schedule D-Part 4 and Part 5) (2001-2015).	1,474,635
(ii)	Remove stock sells with non-positive number of shares or adjusted carrying value.	1,417,644
(iii)	Aggregate sells of the same stocks on each transaction date for each PL insurer.	1,150,677
(iv)	Remove stock sells that cannot be merged with the CRSP database on each transaction date.	907,963
Panel D: Financial Data		
(i)	Obtain PL insurers' financial data from the NAIC InfoPro database (2001-2015).	19,371
(ii)	Remove PL insurers with non-positive net admitted assets.	19,370
(iii)	Remove PL insurers with non-positive net premiums written.	17,030
(iv)	Remove PL insurers with non-positive market value of a common stock portfolio.	7,290
(v)	Remove PL insurers that are neither mutuals nor stocks.	6,350
(vi)	Remove PL insurers without sufficient information to calculate the variables in the regression analysis.	6,103

This table presents the data screenings in our samples. Panels A, B, C, and D report the screen criteria and number of observations in the sample of stock holdings, stock buys, stock sells, and financial data, respectively.

Table 2
Summary Statistics of Stock Holdings and Transactions

	Num of Insurers	Num of Transactions (thousand)	Num of Stocks	Num of Shares (billion)	Value ($ billion)
Panel A: Stock Holdings					
2001	1,026	n/a	3,551	2.5431	93.9519
2002	988	n/a	3,198	2.6628	77.7449
2003	973	n/a	3,208	2.4840	99.3799
2004	928	n/a	3,262	2.5848	108.6402
2005	931	n/a	3,326	2.7292	114.8489
2006	923	n/a	3,387	2.9166	131.9163
2007	923	n/a	3,285	2.9549	133.3732
2008	959	n/a	3,122	2.9065	91.2329
2009	924	n/a	3,405	3.0750	110.9005
2010	917	n/a	3,331	2.8910	117.4033
2011	944	n/a	3,290	3.1199	137.2428
2012	946	n/a	3,332	3.4475	155.1794
2013	956	n/a	3,448	3.6296	205.7128
2014	968	n/a	3,826	3.7026	217.9071
2015	978	n/a	3,887	3.9113	212.0039
Average	952	n/a	3,391	3.0373	133.8292
Panel B: Stock Buys					
2001	907	55.8630	3,057	0.9056	29.7453
2002	865	60.8740	2,868	0.7775	22.4040
2003	866	54.7860	2,999	0.7457	21.9319
2004	861	65.7970	3,367	0.9285	28.6405
2005	864	67.3250	3,297	0.9087	31.3963
2006	868	77.4340	3,436	1.0939	39.1499
2007	846	79.8650	3,553	1.0391	38.7013
2008	900	84.0780	3,218	1.2543	45.2704
2009	875	66.9350	3,461	1.1011	29.5456
2010	801	60.6730	3,318	0.7013	23.2221
2011	857	63.1610	3,453	0.9180	39.3596
2012	855	53.3860	3,149	0.7554	26.8021
2013	866	57.2170	3,197	0.9436	42.6676
2014	875	64.7700	3,836	0.7493	34.9274
2015	885	68.0150	3,944	0.8886	42.9529
Average	866	65.3453	3,344	0.9141	33.1145
Panel C: Stock Sells					
2001	929	53.4780	3,281	0.9449	30.9951
2002	893	57.8520	3,056	0.8942	25.2857
2003	874	48.4540	2,878	0.7674	20.5711
2004	870	57.9250	3,363	0.8565	23.7356
2005	858	55.0270	3,214	0.8569	25.4368
2006	864	70.0700	3,405	1.0325	31.9935
2007	843	77.2220	3,477	0.9917	33.2823
2008	893	80.1080	3,255	1.2407	37.5198
2009	869	62.2510	3,260	1.0203	31.3796
2010	798	54.4810	3,511	0.8620	23.5608
2011	821	58.5970	3,416	0.7356	21.0198
2012	817	54.2610	3,252	0.6675	22.4567
2013	840	56.2290	3,260	0.7942	27.7605
2014	855	59.8730	3,700	0.7012	28.9575
2015	847	62.1350	3,625	0.7021	27.7624

Average	858	60.5309	3,330	0.8712	27.4478

This table presents the summary statistics of stock holdings and transactions (i.e., buys and sells) of PL insurers. Panels A, B, and C report the stock holdings, buys, and sells, respectively, in each year during the sample period (2001-2015) and their averages.

PORTFOLIO TILT REGARDING BETA

As is described in the Section 4 (Empirical Method), we first investigate PL insurers' portfolio beta choice before testing our hypotheses. Specifically, we use the measure of the beta bias (BB) to examine whether they tilt their portfolios toward stocks with certain betas. The tested assets are the PL insurers' common stock holdings at the end of each year during our sample period. The market portfolio is used as the benchmark, and the break points are the beta deciles of the stocks in the market portfolio. Table 3 presents the results from the analysis of the beta bias. Panel A reports the beta bias based on the deciles of the unconditional beta. We find that the PL insurers exhibit a positive beta bias in the lower beta deciles and a negative beta bias in the higher beta deciles. For instance, the means of the beta biases in the first, second, and third beta deciles are 21.94, 32.00, and 17.47 percent, respectively, while the means of the beta biases in the eighth, ninth, and tenth beta deciles are -7.24, -21.16, and -26.85 percent, respectively. We also test the significance of the beta bias in each decile, and the *p*-values suggest that all beta biases are statistically significant except for the beta bias in the fourth decile. Panel B reports the beta bias based on the deciles of the conditional beta. The conditional beta is calculated following equations (12) and (13) with the CRSP daily return data over the prior 12 months. We find that the results stay materially the same. Overall, the PL insurers' beta bias is negatively related to the stock beta, reflecting the portfolio tilt toward low-beta stocks and away from high-beta stocks.

Table 3
Beta Bias

	w_p	w_m	Beta Bias (BB) $(w_p-w_m)/w_m$	*p*-value
Panel A: Unconditional Beta Bias				
1	1.83%	1.47%	21.94%	0.00
2	9.25%	6.98%	32.00%	0.00
3	13.60%	11.62%	17.47%	0.00
4	12.41%	12.50%	-0.72%	0.50
5	13.26%	13.70%	-2.56%	0.01
6	14.04%	13.45%	4.05%	0.00
7	11.60%	12.12%	-4.78%	0.00
8	10.54%	11.39%	-7.24%	0.00
9	8.04%	9.89%	-21.16%	0.00
10	5.43%	6.87%	-26.85%	0.00
Panel B: Conditional Beta Bias				
1	1.67%	1.44%	19.57%	0.00
2	6.72%	5.44%	29.38%	0.00
3	13.52%	11.61%	16.71%	0.00
4	14.59%	14.08%	3.13%	0.00
5	14.58%	13.38%	9.03%	0.00
6	13.27%	12.40%	7.36%	0.00
7	12.89%	13.10%	-1.72%	0.10
8	10.56%	12.01%	-13.24%	0.00
9	7.51%	10.51%	-28.80%	0.00
10	4.68%	6.02%	-24.77%	0.00

This table presents the beta bias in the stock holdings of PL insurers. Panels A and B report the average unconditional and conditional beta biases, respectively. The beta bias (BB) is measured by $(w_p-w_m)/w_m$, where w_p represents the percentage of a PL insurer's portfolio in a beta decile and w_m represents the percentage of the market portfolio in this beta decile. The significance of the mean is tested by a t-test with its p-value reported. The averages of w_p and w_m are also reported.

BETA-LEVERAGE RELATION

To test our hypotheses regarding the beta-leverage relation, we employ the multivariate regressions to examine whether levered PL insurers overweight low-beta stocks. The variables employed in the multivariate regressions are presented in Table 4, and the summary statistics are reported in Table 5. Table 5 shows that the value-weighted unconditional and conditional portfolio betas of PL insurers' common stock portfolios are 0.94 and 0.93, respectively, both of which are less than one, implying that PL insurers tilt their portfolio toward low-beta stocks. The portfolio betas that we find are close to the value-weighted portfolio beta of Berkshire Hathaway (0.91) reported by Frazzini and Pedersen (2014). The average leverage in our sample is 0.53, and it is also consistent with summary statistics reported by other researchers. For example, Colquitt, Sommer, and Godwin (1999) report that the leverage measure has a mean of 0.5840 in their sample.

Before we formally conduct multivariate regressions, we first examine the distribution of the value-weighted portfolio beta across leverage deciles. Figure 1 presents the results. Panel A exhibits the distribution of the means of the unconditional portfolio beta in each leverage decile. We do not observe a negative relation between the portfolio beta and the leverage based on the trend of the distribution. Moreover, in the first four leverage deciles, the relation seems to be positive. Panel B exhibits the distribution of the medians of the unconditional portfolio beta in each leverage decile. We find that while the median of the portfolio beta increases with the leverage in the first four deciles of the leverage, the median decreases with the leverage in the last six deciles. Panels C and D exhibit the distribution of the mean and the median of the conditional portfolio beta, respectively. While panel C shows an overall positive relation between the portfolio beta and the leverage, panel D does not exhibit a significant overall trend. Therefore, from the perspective of the univariate distribution, we do not find evidence for PL insurers betting against beta. We do note that Panel B might suggest that the relation between the portfolio beta and the leverage is non-linear and the negative relation can be observed when the leverage is higher. To address this concern, we also conduct the robustness check using the piecewise regressions following our main multivariate regressions.

As is discussed in the Section 4 (Empirical Methods), we employ three different approaches in the multivariate regressions to test the relation between the portfolio tilt regarding stock beta and the leverage. The first approach uses the value-weighted unconditional and conditional portfolio betas (UN_PTF_BETA and CO_PTF_BETA) as the dependent variable. Table 6 reports the results. We find that the coefficient estimate on the leverage is not significant across all model specifications. Therefore, the leverage is not a significant predictor for the portfolio beta. Instead, we find that the firm size is positively and significantly related to the portfolio beta, implying that large PL insurers tend to hold a portfolio with higher market risk. In addition, the relation between the portfolio beta and the size of the portfolio is negative and significant, suggesting that the PL insurers that hold a larger common stock portfolio tend to choose less market risk exposure. Moreover, the portfolio diversification is positively and significantly related to the portfolio beta in three out of four models.

The second approach uses the proportions of investment in an unconditional and conditional beta decile ($UN\_PRO\_D(1, 2, \dots, 10)$ and $CO\_PRO\_D(1, 2, \dots, 10)$) as the dependent variable. Panel A in Table 7 presents the results based on the unconditional beta deciles. We find that the leverage is positively and significantly related to the proportion of investment in the last beta decile and that it is negatively and significantly related to the proportion of investment in the first beta decile, implying a positive relation between the portfolio beta and the leverage. In addition, we find that the relation between the proportion of the investment in a middle range of the stock beta (i.e., the fourth decile) and the leverage is positive and significant. Panel B in Table 7 presents the results based on the conditional beta deciles. We find that the coefficient estimate on the leverage is not statistically significant except for the first beta decile. In the first beta decile, the coefficient estimate on the leverage is negative and significant, suggesting that PL insurers that use more leverage tend to underweight the low-beta stocks.

The third approach uses the beta bias in each unconditional and conditional beta decile ($UN\_BB\_D(1,2,\ldots,10)$ and $CO\_BB\_D(1,2,\ldots,10)$) as the dependent variable. Panels A and B in Table 8 present the results from the regressions of the beta bias on the leverage in each unconditional and conditional beta decile, respectively. We find that the results reported in panel A are generally consistent with the panel A in Table 7. Specifically, the beta bias in the last decile is positively and significantly related to the leverage, and the beta bias in the first decile is negatively and significantly related to the leverage, rejecting the prediction of the BAB strategy. In addition, the beta bias in the fourth decile is positively related to the leverage. Panel B shows that the coefficient estimate on the leverage is not statistically significant across all conditional beta deciles, suggesting that the leverage is unrelated to the PL insurers' portfolio tilt regarding beta.

As is previously mentioned, it is possible that the negative relation between the portfolio beta and the leverage exists only when the leverage is higher. The panel B of Figure 1 suggests that the 40^{th} percentile is likely a turning point. We follow Morck, Shleifer, and Vishny (1988) and Wruck (1989) and use the piecewise regressions to identify this possible relation for PL insurers with higher leverage. Specifically, the leverage is decomposed into two variables that vary in a lower range and a higher range, respectively. The calculation is as follows,

$$LEV\_GT40 = \begin{cases} 0, & LEV < the\ 40th\ percentile\ of\ LEV \\ LEV, & LEV \geq\ the\ 40th\ percentile\ of\ LEV \end{cases} \quad (21)$$

$$LEV\_LT40 = \begin{cases} 0, & LEV \geq the\ 40th\ percentile\ of\ LEV \\ LEV, & LEV <\ the\ 40th\ percentile\ of\ LEV \end{cases} \quad (22)$$

We reproduce the results of our multivariate regressions using these two decomposed variables for the leverage. If the negative relation between the portfolio beta and the leverage exists only in the higher level of leverage, we would expect to find evidence from the coefficient on LEV_GT40. However, from the unreported tables, we do not find consistent evidence that supports this prediction.

Table 4
Variables and Their Descriptions in Multivariate Analysis of Stock Holdings

Variable Name	Variable Description
UN_PTF_BETA	Value-weighted unconditional portfolio beta.
CO_PTF_BETA	Value-weighted conditional portfolio beta.
UN_PRO_D(1, 2, …, 10)	Proportions of the common stock portfolio in stocks with an unconditional beta in the deciles 1, 2, …, 10, respectively.
CO_PRO_D(1, 2, …, 10)	Proportions of the common stock portfolio in stocks with a conditional beta in the deciles 1, 2, …, 10, respectively.
UN_BB_D(1, 2, …, 10)	Beta biases in stocks with an unconditional beta in the deciles 1, 2, …, 10, respectively.
CO_BB_D(1, 2, …, 10)	Beta biases in stocks with a conditional beta in the deciles 1, 2, …, 10, respectively.
LEV	Leverage, as measured by the ratio of total liabilities to total assets.
AGE	Firm age, as measured by the natural logarithm of the number of years since commencement.
SIZE	Firm size, as measured by the natural logarithm of total net admitted assets.
NPW_SIZE	Size of net premiums written, as measured by the natural logarithm of total net premiums written.
PUBLIC	Public status, as measured by a dummy variable that is equal to 1 for a publicly-traded insurer and 0 for a private insurer.
PTF_MV	Market value of common stock portfolio, as measured by the natural logarithm of the total market value of the common stock portfolio.
PTF_DIV	Portfolio diversification, as measured by the natural logarithm of the number of stocks held by the insurer.
MUTUAL	Organization form, as measured by the dummy variable that is equal to 1 for a mutual insurer and 0 for a stock insurer.
REINSURANCE	Reinsurance ratio, as measured by the ratio of premiums ceded to the sum of direct premiums written and reinsurance assumed.
LONG_TAIL	Weight of long-tail line insurance, as measured by the percentage of net premiums written on long-tail lines.
LINES_DIV	Business line diversification, as measured by the complement of the Herfindahl Index of net premiums written across all business lines.
GEO_DIV	Geographic diversification, measured by the complement of Herfindahl index of direct premiums written across all U.S. states and territories.

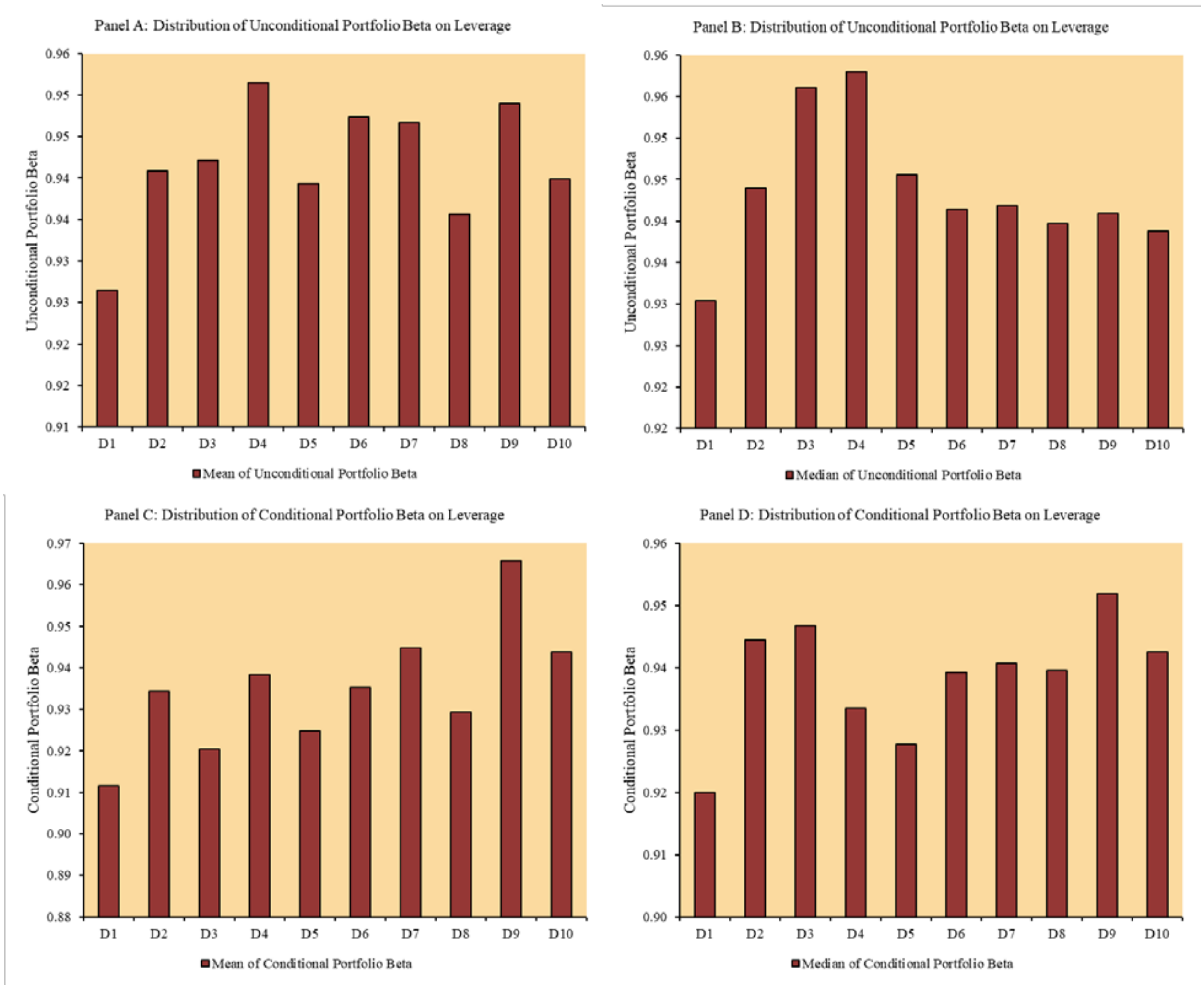
This table reports the variables and their descriptions in the multivariate analysis of stock holdings.

Table 5
Summary Statistics for Multivariate Analysis of Stock Holdings

Variable Name	N	Mean	Median	Min	Max	Std. Dev.	1st Quartile	3rd Quartile
UN_PTF_BETA	6,103	0.9419	0.9429	-0.7209	2.3398	0.1612	0.8543	1.0222
CO_PTF_BETA	6,103	0.9348	0.9380	-1.9031	3.6362	0.2602	0.8258	1.0283
LEV	6,103	0.5260	0.5516	0.0490	0.8944	0.1852	0.4112	0.6642
AGE	6,103	3.6386	3.7377	0.0000	5.3706	1.0788	2.8904	4.6444
SIZE	6,103	17.7603	17.6369	11.5375	23.7304	1.7446	16.5123	18.9793
NPW_SIZE	6,103	16.5710	16.6633	5.0814	22.1558	2.0058	15.3233	17.9743
PUBLIC	6,103	0.0426	0.0000	0.0000	1.0000	0.2020	0.0000	0.0000
PTF_MV	6,103	14.6739	14.7490	1.0986	22.1642	2.3509	13.3006	16.2168
PTF_DIV	6,103	3.1366	3.4012	0.0000	7.3011	1.5367	2.1972	4.1431
MUTUAL	6,103	0.4444	0.0000	0.0000	1.0000	0.4969	0.0000	1.0000
REINSURANCE	6,103	0.2467	0.1871	0.0000	0.8732	0.2164	0.0767	0.3640
LONG_TAIL	6,103	0.7007	0.7978	0.0000	1.0000	0.3249	0.6075	0.9605
LINES_DIV	6,103	0.3493	0.3878	0.0000	0.8537	0.3010	0.0000	0.6470
GEO_DIV	6,103	0.2963	0.0584	0.0000	0.9676	0.3493	0.0000	0.6261

This table presents the summary statistics of the sample in the multivariate analysis of stock holdings. For parsimony, the summary statistics of the proportions and beta biases of the common stock portfolio in stocks in each unconditional or conditional beta decile are omitted, and they can be found in Table 3.

Figure 1
Distribution of Portfolio Beta on Leverage



This figure presents the distribution of insurers' unconditional and conditional portfolio beta on the deciles of their leverage. Panels A and B (C and D) exhibit the distribution of the mean and median of unconditional (conditional) portfolio beta, respectively. The horizontal axis represents the deciles of the leverage, and the vertical axis represents the mean or median of the unconditional or conditional portfolio beta.

Table 6
Effects of Leverage on Portfolio Beta

Dependent Variable: Portfolio Beta (UN_PTF_BETA and CO_PTF_BETA)				
Variables	Unconditional Beta	Unconditional Beta	Conditional Beta	Conditional Beta
INTERCEPT	0.7654***	0.6215**	0.6756***	0.4560
	(0.0411)	(0.2576)	(0.0682)	(0.4875)
LEV	0.0046	0.0419	-0.0194	0.0511
	(0.0221)	(0.0492)	(0.0382)	(0.0846)
AGE	-0.0033	-0.0063	-0.0086	-0.0105
	(0.0047)	(0.0162)	(0.0079)	(0.0262)
SIZE	0.0175***	0.0360**	0.0380***	0.0713**
	(0.0058)	(0.0178)	(0.0102)	(0.0321)
NPW_SIZE	-0.0007	-0.0049	-0.0037	-0.0108
	(0.0039)	(0.0101)	(0.0064)	(0.0167)
PUBLIC	0.0001	-0.0032	0.0078	-0.0089
	(0.0214)	(0.0525)	(0.0398)	(0.0969)
PTF_MV	-0.0133***	-0.0182***	-0.0304***	-0.0492***
	(0.0038)	(0.0067)	(0.0074)	(0.0124)
PTF_DIV	0.0108***	0.0083	0.0263***	0.0281***
	(0.0032)	(0.0051)	(0.0058)	(0.0094)
MUTUAL	-0.0047	0.0713	-0.0093	0.1385
	(0.0085)	(0.0573)	(0.0144)	(0.0951)
REINSURANCE	-0.0344**	-0.0266	-0.0703***	-0.0795
	(0.0161)	(0.0321)	(0.0270)	(0.0514)
LONG_TAIL	-0.0111	0.0156	-0.0181	-0.0069
	(0.0155)	(0.0459)	(0.0260)	(0.0720)
LINES_DIV	-0.0021	0.0303	0.0048	0.0524
	(0.0212)	(0.0371)	(0.0359)	(0.0654)
GEO_DIV	0.0345*	-0.0106	0.0544*	-0.0301
	(0.0178)	(0.0422)	(0.0313)	(0.0715)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes
Adj. R-Squared	0.2583	0.5027	0.1217	0.3854
N. of Obs.	6,103	6,103	6,103	6,103

This table presents the results from the regression of portfolio beta on leverage. The dependent variable is the unconditional and conditional portfolio beta. The other variables are defined in Table 4. The standard errors (in parentheses) are clustered at the insurer level. *, **, and *** denote significance at 10%, 5%, and 1% levels respectively.

Table 7
Effects of Leverage on Proportion of Investment in Stocks in Each Beta Decile

Panel A: Unconditional Beta Deciles

Dependent Variable: Proportion of portfolio in each unconditional beta decile (UN_PRO_D(1, 2, …, 10))										
Variables	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
INTERCEPT	-0.2726**	0.0148	0.0478	0.0986**	-0.0010	0.0101	-0.0510	0.0632	0.0556	-0.0694
	(0.1273)	(0.0572)	(0.0598)	(0.0443)	(0.0412)	(0.0449)	(0.0423)	(0.0453)	(0.0427)	(0.0506)
LEV	-0.1218**	0.0188	-0.0316	0.0677***	0.0060	0.0187	-0.0070	0.0145	-0.0258	0.0476**
	(0.0564)	(0.0266)	(0.0271)	(0.0221)	(0.0211)	(0.0232)	(0.0213)	(0.0232)	(0.0215)	(0.0237)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of Obs.	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103

Panel B: Conditional Beta Deciles

Dependent Variable: Proportion of portfolio in each conditional beta decile (CO_PRO_D(1, 2, …, 10))										
Variables	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
INTERCEPT	-0.1331	0.0915*	0.1487***	0.1396***	-0.0680	-0.1103**	0.0907**	0.1111***	-0.0398	-0.1228**
	(0.0901)	(0.0503)	(0.0561)	(0.0421)	(0.0488)	(0.0498)	(0.0445)	(0.0381)	(0.0428)	(0.0493)
LEV	-0.0716*	0.0117	0.0412	0.0180	-0.0054	-0.0031	-0.0167	0.0101	0.0034	0.0280
	(0.0428)	(0.0241)	(0.0260)	(0.0215)	(0.0249)	(0.0247)	(0.0223)	(0.0194)	(0.0208)	(0.0232)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of Obs.	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103

This table presents the results from the regression of the proportion of investment stocks in each beta decile on the leverage. The dependent variable is the proportion of common stock portfolio in stocks each beta decile. The other variables are defined in Table 4. Panels A and B report the results based on the unconditional and conditional beta deciles, respectively. The regression model is Tobit with random effects. The left-censoring limit is 0, and the right-censoring limit is 1. *, **, and *** denote significance at 10%, 5%, and 1% levels respectively.

Table 8
Effects of Leverage on Beta Bias in Each Beta Decile

Panel A: Unconditional Beta Deciles

Dependent Variable: Beta bias in each unconditional beta decile (UN_BB_D(1, 2, …, 10))

Variables	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
INTERCEPT	-25.6419**	0.2381	-0.3135	-0.2824	-0.7184**	-0.5268	-1.3229***	-0.6720*	-1.1705***	-3.2191***
	(10.4244)	(1.2305)	(0.5397)	(0.3785)	(0.3113)	(0.3504)	(0.3448)	(0.3860)	(0.4354)	(0.7839)
LEV	-8.6526*	0.3123	-0.2693	0.6037***	0.0818	0.0885	-0.0872	0.1011	-0.2576	0.6989*
	(4.6865)	(0.5817)	(0.2474)	(0.1884)	(0.1602)	(0.1795)	(0.1740)	(0.2004)	(0.2166)	(0.3702)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of Obs.	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103

Panel B: Conditional Beta Deciles

Dependent Variable: Beta bias in each conditional beta decile (CO_BB_D(1, 2, …, 10))

Variables	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
INTERCEPT	-15.5370*	-0.9274	0.2392	0.0894	-1.1329***	-1.9612***	0.1832	-0.6608**	-1.5305***	-4.0516***
	(8.3084)	(1.6589)	(0.5514)	(0.3312)	(0.3733)	(0.4117)	(0.3603)	(0.3123)	(0.4321)	(0.8724)
LEV	-5.7820	0.2816	0.3205	0.1864	-0.0764	0.0661	-0.1400	0.0223	-0.0936	0.6713
	(3.9738)	(0.8386)	(0.2621)	(0.1698)	(0.1899)	(0.2052)	(0.1812)	(0.1610)	(0.2104)	(0.4161)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Line FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of Obs.	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103	6,103

This table presents the results from the regressions of the beta bias on the leverage in each beta decile. The dependent variable is the unconditional and conditional beta biases in panels A and B, respectively. The regression model is Tobit with random effects. The left-censoring limit is -1, and the right-censoring limit $(1- w_m)/w_m$, where w_m represents the percentage of the market portfolio in a beta decile. *, **, and *** denote significance at 10%, 5%, and 1% levels respectively. For parsimony, the control variables are omitted in this table.

PERFORMANCE OF THE BAB STRATEGY

In the previous section, we find that the PL insurers' leverage is not negatively related to their portfolio beta, suggesting that these institutional investors do not bet against beta. One possible explanation is that the BAB strategy is not profitable. So, in this section, we attempt to explain why PL insurers do not beta against beta from the perspective of portfolio returns. To examine PL insurers' portfolio returns, we construct the holdings-based calendar-time portfolios, which reflect the actual weight of each stock in PL insurers' holdings. As is discussed in the Section 4 (Empirical Methods), we sort PL insurers' holdings into decile portfolios based on the past market beta using all listed firms for the break points. The high-beta portfolio and the low-beta portfolio are formed at the beginning of July in each year.

First, we use the one-step IV regressions (IV1) to investigate the performance of these portfolios. Table 9 presents the results. "H" represents the high-beta portfolio, "L" represents the low-beta portfolio, and "HL" represents their difference, which is equivalent to a portfolio that is long high-beta stocks and short low-beta stocks (long-short beta portfolio). Following Cederburg and O'Doherty (2016), we conduct regressions in eight cases. For each case, we use the Newey-West (1987) corrected *t*-statistics with a lag of five to statistically assess the portfolio performance.

Case 1 does not incorporate any instruments in its estimation, and thus, the model of case 1 is the unconditional CAPM. The estimated market beta for the low-beta portfolio is 0.29 compared to 1.93 for the high-beta portfolio. The unconditional alpha of the low-beta portfolio (-

0.33 percent per quarter) is greater than that of the high-beta portfolio (-1.57 percent per quarter). The long-short beta portfolio generates an unconditional alpha of -1.24 percent per quarter. However, the *t*-statistics indicate that this unconditional alpha is statistically insignificant, providing no evidence for Frazzini and Pedersen (2014) and other prior literature that finds the beta anomaly (e.g., Black, 1972; Black, Jensen, and Scholes, 1972; Friend and Blume, 1970; Black, 1993; Mehrling, 2005). Therefore, using the holdings-based calendar-time portfolios approach, we find that that the low-beta portfolio does not outperform the high-beta portfolio even when the unconditional CAPM is used. Consequently, the BAB strategy cannot generate positive abnormal returns.

Case 2 to 8 include the instruments in the one-step IV regressions. They refer to the conditional CAPM. Case 2 uses the short-term lagged-component beta (β^{LC3}) as the instrument. Based on the case 2, case 3 adds the indicator variable that is equal to one for the third quarter of each year and zero otherwise ($I_{\{Q3\}}$) and the interaction between the third quarter indicator and the three-month lagged-component beta ($I_{\{Q3\}} \times \beta^{LC3}$). Case 4 includes the short-term and long-term lagged-component beta (β^{LC3} and β^{LC36}) in the instrument set. Building on case 4, case 5 also introduces the third-quarter indicator variable and its interaction with the short-term lagged-component beta. Case 6 incorporates the dividend yield (DY) and the default spread (DS) as the sole instruments, while case 7 also adds the short-term lagged-component beta. Finally, case 8 uses the full information set. Through case 2 to 8, we find that consistent with case 1, the conditional alpha of the long-short beta portfolio of each case is not statistically significant. Therefore, we do not find evidence for the outperformance of the low-beta portfolio in the unconditional CAPM, providing support to Cederburg and O'Doherty (2016). In addition, the table reports a p-value ($p(\alpha_i \leq \alpha_i^U)$) for the one-sided test that the conditional HL alpha (α_i) is less than or equal to the corresponding unconditional alpha (α_i^U). According to the *p*-values, we find that the difference between the unconditional alpha and the conditional alpha is statistically insignificant, implying that the unconditional alpha is not biased.

Second, as is discussed in Section 4 (Empirical Methods), following Cederburg and O'Doherty (2016), we also investigate the portfolio performance in the Fama-French model because the risk-return relation becomes even flatter after controlling for both size and book-to-market (Fama and French, 1992 and 2006). Table 10 presents the results from the one-step IV regressions using the Fama-French three-factor model. Similar to Table 9, Table 10 reports eight cases, in which case 1 refers to the unconditional CAPM and case 2 to 8 refer to the conditional CAPM. Consistent with the results in the one-step IV regressions without the size and value factor, we find no evidence that the low-beta portfolio outperforms the high-beta portfolio in either the unconditional or the conditional CAPM. In addition, the conditional alpha is significantly different from the unconditional alpha only in the case 8, implying that the unconditional alpha is biased in this case.

Last, we conduct the two-step IV regressions (IV2) to examine the portfolio performance. Table 11 reports the results. Consistent with Table 9 and Table 10, the eight cases in Table 11 also do not support the beta anomaly. In particular, case 1 indicates that the beta anomaly does not exist even in the unconditional CAPM. Again, we find that the difference between the conditional alpha and the unconditional alpha is not statistically significant.

To check the robustness of our results above, we also analyze the performance of the high-beta and low-beta portfolios of PL insurers with high (top quartile) and low (bottom quartile) leverage individually in two subsamples. From the unreported tables, we find that the results are qualitatively the same as those from the overall sample. Taken together, we find no evidence that the PL insurers' low-beta portfolio outperforms their high-beta portfolio, implying that it does not pay to bet against beta.

Table 9
Instrumental Variables Regressions (IV1)

Case		α_i^{IV1}	$p(\alpha_i \leq \alpha_i^U)$	Adj R^2
1	L	-0.0033		0.1077
		(-0.3104)		
	H	-0.0157		0.7484
		(-1.2746)		
	HL	-0.0124	n/a	
		(-0.8108)		
2	L	-0.0038		0.0937
		(-0.3504)		
	H	-0.0120		0.7534
		(-1.0065)		
	HL	-0.0082	0.3257	
		(-0.5303)		
3	L	-0.0044		0.0716
		(-0.3904)		
	H	-0.0073		0.7760
		(-0.6323)		
	HL	-0.0029	0.1603	
		(-0.1896)		
4	L	-0.0039		0.0776
		(-0.3390)		
	H	-0.0119		0.7520
		(-0.9880)		
	HL	-0.0080	0.3679	
		(-0.5056)		
5	L	-0.0044		0.0544
		(-0.3721)		
	H	-0.0073		0.7725
		(-0.6276)		
	HL	-0.0029	0.1672	
		(-0.1841)		
6	L	-0.0030		0.0787
		(-0.2862)		
	H	-0.0138		0.7686
		(-1.4076)		
	HL	-0.0109	0.7717	
		(-0.7204)		
7	L	-0.0035		0.0639
		(-0.3261)		
	H	-0.0126		0.7655
		(-1.1921)		
	HL	-0.0092	0.5791	
		(-0.5943)		
8	L	-0.0047		0.0227
		(-0.4024)		

H	-0.0086		0.7825
	(-0.7954)		
HL	-0.0039	0.2965	
	(-0.2497)		

This table presents the results from the one-step IV regressions (IV1) for PL insurers' decile portfolios using all CRSP stocks to determine break points of past market betas. The formation-period betas are estimated using 12 months of the CRSP daily data, and the portfolios are rebalanced at the beginning of each July. "H" represents the high-beta portfolio, "L" represents the low-beta portfolio, and "HL" represents their difference (long-short beta portfolio). The regression model is as follows,

$$R_{i,\tau} = \alpha_i^{IV1} + \left(\gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1}\right) R_{m,\tau} + u_{i,\tau}$$

where $R_{i,\tau}$ represents the quarterly buy-and-hold excess return for portfolio i over quarter τ, $R_{m,\tau}$ represents the quarterly buy-and-hold excess return for the market portfolio over quarter τ, and $Z_{i,\tau-1}$ represents a $k \times 1$ vector of instruments for portfolio i over quarter τ. The instruments $Z_{i,\tau-1}$ include the three-month and 36-month lagged-component betas (β^{LC3} and β^{LC36}), an indicator variable that is equal to one for the third quarter of each year and zero otherwise ($I_{\{Q3\}}$), the interaction between the third quarter indicator and the three-month lagged-component beta ($I_{\{Q3\}} \times \beta^{LC3}$), the log dividend yield (DY), and the default spread (DS). Following Cederberg and O'Doherty (2016), the results of eight cases are reported. Case 1 refers to the unconditional CAPM, and cases 2 to 8 refer to the conditional CAPM. The New-West (1987) corrected *t*-statistics with a lag length equal to five are reported in the parentheses. For each conditional model, the table also reports a *p*-value ($p(\alpha_i \leq \alpha_i^U)$) for the one-sided test that the conditional HL alpha (α_i) is less than or equal to the corresponding unconditional alpha (α_i^U).

Table 10
Fama-French Model Regressions

Case		α_i^{IV1}	$p(\alpha_i \leq \alpha_i^U)$	Adj R^2
1	L	-0.0035		0.0831
		(-0.3109)		
	H	-0.0173*		0.7957
		(-1.7597)		
	HL	-0.0138	n/a	
		(-0.9525)		
2	L	-0.0043		0.0406
		(-0.3457)		
	H	-0.0141		0.7991
		(-1.3684)		
	HL	-0.0098	0.4387	
		(-0.6564)		
3	L	-0.0054		-0.0683
		(-0.3696)		
	H	-0.0112		0.8169
		(-0.8418)		
	HL	-0.0058	0.3504	
		(-0.3567)		
4	L	-0.0042		-0.0146
		(-0.3057)		
	H	-0.0139		0.7957
		(-1.4601)		
	HL	-0.0097	0.4575	
		(-0.6261)		
5	L	-0.0059		-0.1347
		(-0.3674)		
	H	-0.0106		0.8089
		(-0.7956)		
	HL	-0.0047	0.3063	
		(-0.2695)		
6	L	-0.0045		0.1443
		(-0.3652)		
	H	-0.0100		0.7911
		(-0.6740)		
	HL	-0.0055	0.3615	
		(-0.3369)		
7	L	-0.0055		0.1156
		(-0.3583)		
	H	-0.0090		0.7918
		(-0.6449)		
	HL	-0.0035	0.2948	
		(-0.2010)		
8	L	-0.0108		0.0087
		(-0.5340)		
	H	-0.0009		0.8324
		(-0.0498)		
	HL	0.0099	0.0640	

(0.5335)

This table presents the results from the one-step IV regressions (IV1) using the Fama-French (1993) three-factor model for PL insurers' decile portfolios using all CRSP stocks to determine break points of past market betas. The formation-period betas are estimated using 12 months of the CRSP daily data, and the portfolios are rebalanced at the beginning of each July. "H" represents the high-beta portfolio, "L" represents the low-beta portfolio, and "HL" represents their difference (long-short beta portfolio). The regression model is as follows,

$$R_{i,\tau} = \alpha_i^{IV1} + \left(\lambda_{i,0} + \lambda_{i,1}' Z_{i,\tau-1}^{\lambda}\right) R_{m,\tau} + \left(\theta_{i,0} + \theta_{i,1}' Z_{i,\tau-1}^{\theta}\right) R_{smb,\tau} + (\eta_{i,0} + \eta_{i,1}' Z_{i,\tau-1}^{\eta}) R_{hml,\tau} + \mu_{i,\tau}$$

where $R_{i,\tau}$ represents the quarterly buy-and-hold excess return for portfolio i over quarter τ, $R_{m,\tau}$ represents the quarterly buy-and-hold excess return for the market portfolio over quarter τ, $R_{smb,\tau}$ represent the quarterly size factor return over quarter τ, $R_{hml,\tau}$ represents the quarterly value factor return over quarter τ, and $Z_{i,\tau-1}$ represents a $k \times 1$ vector of instruments for portfolio i over quarter τ. The instruments $Z_{i,\tau-1}$ include the three-month and 36-month lagged-component betas ($\beta^{LC3}$and β^{LC36}), an indicator variable that is equal to one for the third quarter of each year and zero otherwise ($I_{\{Q3\}}$), the interaction between the third quarter indicator and the three-month lagged-component beta ($I_{\{Q3\}} \times \beta^{LC3}$), the log dividend yield (DY), and the default spread (DS). Following Cederberg and O'Doherty (2016), the results of eight cases are reported. Case 1 refers to the unconditional CAPM, and cases 2 to 8 refer to the conditional CAPM. The New-West (1987) corrected *t*-statistics with a lag length equal to five are reported in the parentheses. For each conditional model, the table also reports a *p*-value ($p(\alpha_i \leq \alpha_i^U)$) for the one-sided test that the conditional HL alpha (α_i) is less than or equal to the corresponding unconditional alpha (α_i^U).

Table 11
Instrumental Variables Regressions (IV2)

Case		α_i^{IV2}	$p(\alpha_i \leq \alpha_i^U)$	Adj R^2
1	L	-0.0033		0.1077
		(-0.3104)		
	H	-0.0157		0.7484
		(-1.2746)		
	HL	-0.0124	n/a	
		(-0.8108)		
2	L	-0.0038		0.0937
		(-0.3504)		
	H	-0.0120		0.7534
		(-1.0065)		
	HL	-0.0082	0.3257	
		(-0.5303)		
3	L	-0.0041		0.0969
		(-0.3774)		
	H	-0.0131		0.7665
		(-1.1011)		
	HL	-0.0089	0.4416	
		(-0.5924)		
4	L	-0.0033		0.0929
		(-0.2993)		
	H	-0.0121		0.7532
		(-1.0097)		
	HL	-0.0088	0.3819	
		(-0.5709)		
5	L	-0.0033		0.0940
		(-0.3025)		
	H	-0.0132		0.7657
		(-1.1041)		
	HL	-0.0099	0.5580	
		(-0.6561)		
6	L	-0.0033		0.0921
		(-0.3112)		
	H	-0.0136		0.7539
		(-1.2531)		
	HL	-0.0102	0.4768	
		(-0.6685)		
7	L	-0.0033		0.0932
		(-0.3018)		
	H	-0.0115		0.7582
		(-1.0507)		
	HL	-0.0082	0.3416	
		(-0.5345)		
8	L	-0.0034		0.0949
		(-0.3099)		
	H	-0.0121		0.7662
		(-1.0815)		
	HL	-0.0087	0.3643	

(-0.5797)

This table presents the results from the two-step IV regressions (IV2) for PL insurers' decile portfolios using all CRSP stocks to determine break points of past market betas. The formation-period betas are estimated using 12 months of the CRSP daily data, and the portfolios are rebalanced at the beginning of each July. "H" represents the high-beta portfolio, "L" represents the low-beta portfolio, and "HL" represents their difference (long-short beta portfolio). The first stage model is as follows,

$$\hat{\beta}_{i,\tau} = \delta_{i,0} + \delta'_{i,1} Z_{i,\tau-1} + e_{i,\tau}$$

where $\hat{\beta}_{i,\tau}$ represents the estimated quarterly portfolio beta for portfolio i over quarter τ and $Z_{i,\tau-1}$ represents a $k \times 1$ vector of instruments for portfolio i over quarter τ. The instruments $Z_{i,\tau-1}$ include the three-month and 36-month lagged-component betas (β^{LC3} and β^{LC36}), an indicator variable that is equal to one for the third quarter of each year and zero otherwise ($I_{\{Q3\}}$), the interaction between the third quarter indicator and the three-month lagged-component beta ($I_{\{Q3\}} \times \beta^{LC3}$), the log dividend yield (DY), and the default spread (DS). The fitted betas from this regression, $\tilde{\beta}_{i,\tau}$, are used in the second-stage return regression. The second stage model is as follows,

$$R_{i,\tau} = \alpha_i^{IV2} + \left(\phi_{i,0} + \phi_{i,1}\tilde{\beta}_{i,\tau}\right) R_{m,\tau} + v_{i,\tau}$$

where $R_{i,\tau}$ represents the quarterly buy-and-hold excess return for portfolio i over quarter τ and $R_{m,\tau}$ represents the quarterly buy-and-hold excess return for the market portfolio over quarter τ. Following Cederberg and O'Doherty (2016), the results of eight cases are reported. Case 1 refers to the unconditional CAPM, and cases 2 to 8 refer to the conditional CAPM. The New-West (1987) corrected *t*-statistics with a lag length equal to five are reported in the parentheses. For each conditional model, the table also reports a *p*-value ($p(\alpha_i \leq \alpha_i^U)$) for the one-sided test that the conditional HL alpha (α_i) is less than or equal to the corresponding unconditional alpha (α_i^U).

CONCLUSION

The beta anomaly is one of the most widely documented anomalies in the asset pricing literature (e.g., Black, 1972; Black, Jensen, and Scholes, 1972; Friend and Blume, 1970; Black, 1993; Mehrling, 2005). Based on the beta anomaly, Frazzini and Pedersen (2014) propose the betting-against-beta (BAB) strategy which argues that it pays to apply leverage and tilt toward low-beta stocks and that investors who use leverage should tilt their portfolios toward low-beta stocks. They also provide anecdotal evidence that the portfolio beta choice of investors in the real world is consistent with the prediction of the BAB strategy. However, the beta anomaly is challenged by Cederburg and O'Doherty (2016). They find that the differences in conditional alphas across beta portfolios are statistically insignificant, suggesting that the conditional CAPM can resolve the beta anomaly. Given the theoretical basis for the BAB is undermined by the conditional CAPM, the relation between the portfolio tilt toward low-beta stocks and the leverage remains inconclusive.

In this study, we investigate the proposition of the BAB strategy regarding the relation between the portfolio beta and leverage using the U.S. property-liability (PL) insurance companies' common stock holdings. Through our empirical analysis, we find that the PL insurers' portfolio beta choice is not negatively related to their leverage, suggesting that they do not bet against beta. In addition, we explore the explanation by examining the performance of PL insurers' low-beta and high-beta portfolios with a holdings-based calendar-time portfolio approach. We find that the differences in neither unconditional alphas nor conditional alphas across the beta portfolios are statistically significant, implying that the PL insurers' low-beta portfolio does not outperform their high-beta portfolio. Overall, the results in our study indicate that the BAB does not exist.

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ESSAY III

EFFECTS OF MARKET CONCENTRATION ON CASH HOLDINGS: EMPIRICAL EVIDENCE FROM THE U.S. PROPERTY-LIABILITY INSURANCE INDUSTRY

INTRODUCTION

A growing body of literature indicates that important corporate decisions are influenced by market concentration (e.g., Harris, 1998; DeFond and Park, 1999; Botosan and Harris, 2000; Fee and Thomas, 2004; Hou and Robinson, 2006; Haushalter, Klasa, and Maxwell, 2007; Kale and Shahrur, 2007; Karuna, 2007). In particular, many studies have shown that market concentration plays an important role in shaping a firm's cash holdings policy (e.g., Haushalter, Klasa, and Maxwell, 2007; Hoberg, Phillips, and Prabhala, 2014). However, there is considerable theoretical and empirical disagreement as to both how and why market concentration affects corporate cash holdings. In this article, we investigate this relation in the U.S. property-liability insurance industry and attempt to reconcile competing theoretical predictions and conflicting empirical evidence in the prior literature. The unique reporting requirements in the insurance industry grant us several natural advantages to avoid the well-known public firm bias and segment reporting biases that are present in previous studies. They also provide us with highly disaggregated state-line data, which make a more refined measure of market concentration possible.

Theory suggests that market concentration affects cash holdings due to predation risk and financial constraints. The predation risk theory implies that cash holdings provide an important source of financial flexibility that helps firms mitigate the risk of losing investment opportunities and market share to rivals (e.g., Bolton and Scharfstein, 1990; Haushalter, Klasa, and Maxwell, 2007). Given that predation is more likely to occur in more oligopolistic industries (e.g., Froot, Scharfstein, and Stein, 1993; Kovenock and Phillips, 1997; Zingales, 1998), the predation risk theory implies that market concentration is positively related to cash holdings. The financial constraint theory argues that market competition reduces the profitability of assets in place and thus increases the risk that firms cover their unexpected operating losses by raising capital (Morellec, Nikolov, and Zucchi, 2014). Due to the higher cost of external capital, cash holdings become more valuable as competition increases. Since competition is less intensive in a more concentrated market, the financial constraint theory implies a negative relation between cash holdings and market concentration.

Empirically, Haushalter, Klasa, and Maxwell (2007) find that firms hold more cash in a more concentrated market, supporting the prediction of their predation risk theory. Alternatively, Morellec, Nikolov, and Zucchi (2014) show that market concentration is negatively related to the cash holdings of a firm, providing support for their financial constraint-based theory. As evidenced by the competing theoretical predictions and conflicting empirical findings[37] in the literature, the role played by market concentration in determining a firm's cash holdings policy is still inconclusive. We believe the U.S. property-liability insurance industry is an ideal setting to investigate the relation between market concentration and cash holdings due to regulatory reporting requirements that are not otherwise present in other industries.

First, we benefit from the richness of the insurance statutory data because all licensed insurers (both private and public) are required to file their statutory statements on an annual basis, and thus, we are able to compute market concentration measures based on all firms in this industry. By contrast, prior empirical work has focused almost exclusively on publicly-traded

[37] A strand of closely related literature is focused on the effects of market concentration on the value of cash holdings. Their evidence is also mixed. For example, Alimov (2014) shows that the relation between the value of cash holdings and market concentration is negative. However, Chi and Su (2016) report that different Herfindahl indices (HHIs) give different value implications for cash holdings, and the negative and significant relation is constrained to only a limited set of concentration measures.

firms that are required by the Securities and Exchange Commission (SEC) to file annual statements. Ali, Klasa, and Yeung (2009) reexamine previous studies that use Compustat-based industry concentration measures, which exclude data on private firms, and find that these are poor measures of market concentration. They also show that the significant results reported by previous studies are attributable to these measures proxying for other industry characteristics that are correlated with their dependent variables rather than a real economic relation. Therefore, with data available for all firms in the U.S. property-liability insurance industry, we are able to avoid the "public firm bias" warned of by Ali, Klasa, and Yueng (2009).

Second, unlike managers of unregulated firms who exercise considerable discretion in segment-level revenue allocation, managers of insurers do not need to exercise discretion in revenue allocation as revenue (i.e., premiums) is directly linked to specific lines of business. Therefore, our study avoids the well-known segment reporting biases (i.e., minimum unit size, self-reporting errors, and ad-hoc categorization by management) that affect business segment disclosure by unregulated firms.[38]

Third, insurers are required to report their highly disaggregated premium (revenue) data, while firms in unregulated industries are not required to provide data in such detail. Specifically, insurers' statutory statements have a unique section (i.e., "Exhibit of Premiums and Losses (Statutory Page 14)") that reports the data for each line of business within each state. They provide us with the most disaggregated data in a bi-dimensional space, implying that we are able to observe an insurer's business in each state-line combination.[39] Therefore, we can more accurately identify an insurer's market space and compute a more accurate measure of market concentration than prior studies that use concentration measures based on primary SIC codes.

[38] For more detail, see Villalonga (2004) and Botosan and Stanford (2005).

[39] For instance, we are able to directly observe the dollar amount of premiums written by a given insurer in the commercial automobile insurance line in Texas or in the homeowners' line in California.

Taking advantage of the unique reporting requirements discussed above, we investigate the relation between cash holdings policy and market concentration in the U.S. property-liability insurance industry. We propose a refined market concentration measure, *market space weighted concentration*, which more accurately reflects a firm's state-line market space. Through our empirical analysis, we provide evidence in support of the predation risk theory. Specifically, insurers exposed to higher market concentration tend to hold a larger cash balance. In addition, we examine whether higher cash holdings are used to hedge predation risk. We find that an increase in cash holdings is associated with faster future growth when market concentration is higher, providing further support for the predation risk theory. We also show that this effect is significant only when cash holdings are below the target level, implying that excessive cash holdings are not optimal.

Our study contributes to the literature in two ways. First, we help to resolve the previous dispute about the relation between market concentration and cash holdings policy. Second, we propose a refined measure of market concentration by which a firm's state-line market space can be more accurately captured.

Our article is clearly distinct from the other studies on cash holdings in the insurance literature. In one of the earliest papers in the insurance literature, Colquitt, Sommer, and Godwin (1999) investigate the determinants of cash holdings by property-liability insurers and identify multiple factors that play an important role in shaping an insurer's cash holdings policy. Hsu, Huang, and Lai (2015) study the role played by the board and the finance committee in the cash holdings of U.S. property-liability insurers. They find that insurers with a higher proportion of outsiders on the board and the financial committee tend hold more cash. Most recently, Xie, Wang, Zhao, and Lu (2017) investigate the difference in cash holdings between publicly-traded insurers and private insurers and find that public insurers tend to hold less cash than private stock insurers.[40] While these prior studies examine the effects of corporate governance, listing status, and other factors on insurers' cash holdings, we focus on the role of market concentration in shaping their cash holdings policy and find that the cash holding decision is also significantly related to market concentration.

The remainder of this paper is organized as follows. We first present our hypotheses. Next, we describe the empirical methods employed to test our hypotheses and then describe our data and sample. Finally, we present and discuss our results, followed by our conclusion.

[40] Their findings differ from the prior literature for non-financial firms which finds the opposite (e.g., Gao, Harford, and Li, 2013; Acharya and Xu, 2017). They argue that public insurers hold less cash because they have a smaller precautionary demand for cash due to their access to equity capital.

HYPOTHESES DEVELOPMENT

Predation Risk Theory

The first strand of theories regarding the relation between market concentration and cash holdings propose that a firm's cash holding policy is influenced by predation risk (e.g., Bolton and Scharfstein, 1990; Froot, Scharfstein, and Stein, 1993; Haushalter, Klasa, and Maxwell, 2007). When a firm cannot fully take advantage of its investment opportunities, it risks losing not only these opportunities but also market share to its rivals (Haushalter, Klasa, and Maxwell, 2007). A firm's ability to finance investments with internal funds is a key determinant of its product market success because the internal funds can mitigate predation risk (Bolton and Scharfstein, 1990). Bolton and Scharfstein (1990) formalize the "long-purse" (or "deep-pockets") theory of predation risk and argue that cash holdings grant a firm financial flexibility in the product markets to effectively counter predatory threats by its rivals or prevent entry of new competitors. Previous literature has shown that cash holdings are an effective risk management tool of predation risk (e.g., Opler, Pinkowitz, Stulz, Williamson , 1999; Harford, Mikkelson, and Partch, 2003; Mikkelson and Partch, 2003; Almeida, Campello, and Weisbach, 2004). For example, Opler et al., (1999) find that firms with strong growth opportunities and riskier cash flows hold a larger cash balance. Mikkelson and Partch (2003) show that firms with high financing costs and more growth opportunities hold more cash to reduce underinvestment problems. Almeida, Campello, and Weisbach (2004) find that financially constrained firms hold more cash during recessions.

Froot, Scharfstein, and Stein (1993) further propose that a firm's exposure to predation risk is determined by the interdependence of its investment opportunities with its product market competitors. Specifically, a firm with greater investment opportunity interdependence with its rivals is exposed to higher predation risk. Consistent with the proposition of Froot, Scharfstein, and Stein (1993), Kovenock and Phillips (1997) and Zingales (1998) both find that predation is more likely to occur in more oligopolistic industries in which the interdependence is more prominent. Thus, Haushalter, Klasa, and Maxwell (2007) argue that firms exposed to high market concentration are expected to hold more cash to manage the predation risk. In their empirical test, they find consistent evidence that cash holdings increase with market concentration. Following their study, we argue that higher market concentration indicates greater interdependence of investment opportunities,[41] which induce higher predation risk. Therefore, we expect that insurers hold more (less) cash in a more (less) concentrated market. The hypothesis can be presented as follows,

Hypothesis 1 (Predation Risk Hypothesis): *Market concentration is positively related to cash holdings.*

Financial Constraint Theory

Morellec, Nikolov, and Zucchi (2014) argue that market competition has an impact on cash holdings through financial constraints. To illustrate this relation, they develop a dynamic model of cash management and propose their financial constraint-based theory. In their model, firms are exposed to financing constraints and external financing is costly. Their model

[41] Investment opportunities may include product or geographic expansion through either organic growth or acquisitions, and cash holdings can be used to take advantage of these opportunities when they emerge (Hsu, Huang and Lai, 2015; Xie et al., 2017).

demonstrates that the profitability of assets in place decreases with the intensity of the market competition. Therefore, compared to firms in a less competitive market, firms in a more competitive market have a greater demand for raising funds in order to cover their potential losses and avoid inefficient closure (e.g., liquidating assets at discounts). In other words, firms exposed to higher market competition are more likely to face financing difficulties. Since external capital is more expensive than internal capital, cash holdings are more valuable for firms in a highly competitive market, and the optimal level of cash holdings should increase with the intensity of market competition. Given that market concentration can be viewed as a proxy for market competition, the financial constraint-based theory suggests a negative relation between cash holdings and market concentration.[42] Morellec, Nikolov, and Zucchi (2014) also empirically test their financial constraint theory and find that cash holdings are negatively related to market concentration. Taken together, in our setting, the financial constraint theory implies that insurers should hold more (less) cash in a less (more) concentrated market. This hypothesis is stated as follows,

Hypothesis 2 (Financial Constraint Hypothesis): *Market concentration is negatively related to cash holdings.*

[42] Economists have long used market concentration as a proxy for product market competition (e.g., Valta, 2012; Hoberg and Phillips, 2010a; Hoberg and Phillips, 2010b; Hoberg, Phillips and Prabhala, 2014). The greater market concentration, the less competitive the product market.

EMPIRICAL METHODS

To examine the relation between market concentration and cash holdings, we first follow the empirical method in Colquitt, Sommer, and Godwin (1999) and Hsu, Huang, and Lai (2015) and employ the linear regression model as our baseline model. The model is shown as follows:

$$Cash\ Holdings_{i,t} = f(Market\ Concentration_{i,t}, Controls_{i,t}) \quad (1)$$

Cash Holding Measure

Consistent with Colquitt, Sommer, and Godwin (1999) and Hsu, Huang, and Lai (2015), an insurer's cash holdings (CASH) are measured by the ratio of cash and short-term investments to total invested assets.

Market Concentration Measure

In the insurance literature, researchers use different measures to measure market concentration. For example, Shim (2017) employs the industry Herfindahl index (HHI) and industry concentration ratios to gauge the market concentration. Liebenberg and Sommer (2008) and Berry-Stölzle, Liebenberg, Ruhland, and Sommer (2012) measure market concentration exposed by an insurer by its weighted average of business line-specific Herfindahl indexes. For an insurer that writes homeowners' insurance in Mississippi, the industry-wide concentration measures used by Shim (2017) capture exposure to market concentration in the entire U.S.

property-liability insurance industry, and the business line weighted concentration measure used by Liebenberg and Sommer (2008) and Berry-Stölzle et al., (2012) captures exposure to market concentration in the entire U.S. homeowners' insurance market. In this study, we attempt to improve the existing measures and capture an insurer's exposure to market concentration in its exact state-line market space (e.g., the homeowners' insurance in Mississippi in the above example). Taking advantage of the detailed data reported for each business line within each state from the U.S. property-liability insurance industry, we propose a market concentration measure, which we refer to as *market space weighted concentration*. Our measure offers the most accurate reflection of market concentration to which an insurer is exposed because it provides the narrowest definition of a market that is possible using insurers' statutory statements. To illustrate, we present the state-line market space of Donegal Insurance Group in 2015 in Figure 1. Figure 1 shows that Donegal underwrites in only 11 out of 22 lines and 21 out of 56 states and territories.[43] This illustration is a fair representation of what is observed in the U.S. PL insurance industry – firms write business in various lines and states and concentration varies considerably across geographic location, lines, and insurers.

The "Exhibit of Premiums and Losses (Statutory Page 14)" in the statutory statements of the U.S. property-liability insurance companies provides detailed data of direct premiums written on each business line within each state. We follow Berry-Stölzle et al., (2012) and combine similar lines of business to create a total of 22 unique lines.[44] Building on the business line

[43] The 56 States and territories include the 50 U.S. states, the District of Columbia, America Samoa, Guam, Puerto Rico, U.S. Virgin Islands, and the Northern Mariana Islands.
[44] Consistent with Berry-Stölzle et al., (2012), we aggregate similar business lines and identify 22 distinct lines that are written by property-liability insurers: (1) accident and health, (2) aircraft, (3) auto, (4) boiler and machinery, (5) burglary and theft, (6) commercial multiple peril, (7) credit, (8) earthquake, (9) farmowners' multiple peril, (10) financial guaranty, (11) fidelity, (12) fire and allied lines, (13) homeowners' multiple peril, (14) inland marine, (15) medical professional liability, (16) mortgage guaranty, (17) ocean marine, (18) other, (19) other liability, (20) products liability, (21) surety, and (22) workers' compensation. We report two fewer distinct lines than Berry-

weighted concentration measure (WCONC) used by Liebenberg and Sommer (2008) and Berry-Stölzle et al., (2012), the market space weighted concentration (MS_WCONC) is calculated as follows,

$$HHI_{j,s,t} = \sum_{i=1}^{n_{j,s,t}} \left(\frac{DPW_{i,j,s,t}}{DPW_{j,s,t}}\right)^2 \quad (2)$$

$$w_{i,j,s,t} = \frac{DPW_{i,j,s,t}}{DPW_{i,t}} \quad (3)$$

$$MS\_WCONC_{i,t} = \sum_{s=1}^{56} \sum_{j=1}^{22} w_{i,j,s,t} \times HHI_{j,s,t} \quad (4)$$

where $DPW_{i,j,s,t}$ is the direct premiums written by insurer *i* in line *j* in state *s* at year *t*, $DPW_{j,s,t}$ is the total direct premiums written in line *j* in state *s* at year *t*, and $DPW_{i,t}$ is the total direct premiums written by insurer *i* at year *t*. The number of insurers that have business in line *j* in state *s* at year *t* is represented as $n_{j,s,t}$. $HHI_{j,s,t}$ represents the Herfindahl index of direct premiums written for line *j* in state *s* at year *t*. $w_{i,j,s,t}$ represents the weight of insurer *i*'s business in line *j* in state *s* at year *t*.

We also create an alternative version of market space weighted concentration (MS_WC4) using the four-firm concentration ratio to measure the market concentration in each state-line segment.[45] The calculation is as follows,

$$C4_{j,s,t} = \frac{\sum_{i=1}^{4} DPW_{i(Four\ Largest),j,s,t}}{DPW_{j,s,t}} \quad (5)$$

$$w_{i,j,s,t} = \frac{DPW_{i,j,s,t}}{DPW_{i,t}} \quad (6)$$

$$MS\_WC4_{i,t} = \sum_{s=1}^{56} \sum_{j=1}^{22} w_{i,j,s,t} \times C4_{j,s,t} \quad (7)$$

Stölzle et al., (2012) because the "Exhibit of Premiums and Losses (Statutory Page 14)" does not report information for "international" or "reinsurance" lines of business.

[45] The concentration ratio has been widely used in the literature (e.g., Montgomery, 1985; Chidambaran, Pugel, and Saunders, 1997; Bajtelsmit and Bouzouita, 1998; Pope and Ma, 2008; Shim, 2017; Bayar et al., 2018).

where $DPW_{i(Four\ Largest),j,s,t}$ is the direct premiums written by the top-four largest insurers i in line j in state s at year t, $DPW_{j,s,t}$ is the total direct premiums written in line j in state s at year t, $DPW_{i,j,s,t}$ is the direct premiums written by insurer i in line j in state s at year t, and $DPW_{i,t}$ is the total direct premiums written by insurer i at year t. $C4_{j,s,t}$ represents the four-firm concentration ratio of direct premiums written for line j in state s at year t. $w_{i,j,s,t}$ represents the weight of insurer i's business in line j in state s at year t. A higher value for both the MS_WCONC and MS_WC4 variables is indicative of a greater level of market concentration and thus a lower level of market competition.

Control Variables

Variables in Colquitt, Sommer, and Godwin (1999): We include the standard control variables specified by Colquitt, Sommer, and Godwin (1999) in our models. The determinants of cash holdings in their study include firm size (SIZE), financial strength (FIN_STREN), group status (GROUP), volatility of cash flows (VOL_CF), duration of liabilities (DURATION), ownership structure (STOCK), leverage (LEVERAGE), investment opportunities (INV_OPT), non-invested assets (NON_INV_AT), and common stock holdings (COM_STOCK).[46]

Firm Age: Hsu, Huang, and Lai (2015) argue that older firms are able to generate more cash. Therefore, we expect a positive relation between firm age and cash holdings. Because the volatility of cash flows (VOL_CF) is measured as the standard deviation of net cash flows from operations over the previous five years, we follow Hsu, Huang, and Lai (2015) and measure firm

[46] The motivations for these variables are presented on pages 404-409 in Colquitt, Sommer, and Godwin (1999).

age (AGE) by the natural logarithm of the difference between an insurer's age and five.[47] For an insurance group, the age is based on the age of its oldest affiliate (Berry-Stölzle et al., 2012).

Dividends: According to Hsu, Huang, and Lai (2015), insurers that pay dividends will have less cash.[48] Therefore, we expect a negative relation between dividend payments and cash holdings. Because we analyze the cash holdings for both mutual and stock insurers, we consider dividend payments to stockholders and policyholders. We measure the dividend payment through the inclusion of a dummy variable (DIVIDEND) that is equal to 1 for an insurer that pays a cash dividend to its stockholders or policyholders in a given year and 0 otherwise.

Public Status: Xie, Wang, Zhao, and Lu (2017) summarize two strands of literature that predict differences in cash holdings between public firms and private firms. In terms of the precautionary motive of cash holdings, prior literature argues that compared to private firms, public firms have better access to the equity capital markets and they can also raise debt capital at a lower cost (e.g., Pagano, Panetta, and Zingales, 1998; Brau and Fawcett, 2006; Xie, 2010; Saunders and Steffen, 2011). Therefore, public (private) firms are expected to have a lower (higher) precautionary demand for cash holdings. However, many studies show that agency conflicts between shareholders and managers are less prevalent among private firms because private firms are closely held, they often have large lenders, and their ownership is less dispersed (e.g., Ang, Cole, and Lin, 2000; Badertscher, Shroff, and White, 2013; Gao, Harford, and Li, 2013; Asker, Farre-Mensa, and Ljungqvist, 2015). Collectively, the relation between public status and cash holdings is indeterminate. We measure the public status by including a dummy variable (PUBLIC) that is equal to 1 for publicly-traded insurers and 0 for private insurers.

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[47] As a robustness check, we also calculate firm age without subtracting five. The results are materially similar to those presented in this paper.

[48] Dividend paying firms requiring access to liquid assets may do so by reducing dividend payments. This allows these firms to hold less cash than firms that do not pay dividends (Opler et al., 1999).

Reinsurance: According to Colquitt, Sommer, and Godwin (1999), riskier insurers have a greater demand for cash holdings. Cole and McCullough (2006) argue that insurers purchase reinsurance to shift risk to reinsurers, thus reducing underwriting risk and the probability of bankruptcy. Therefore, a negative relation is expected between the use of reinsurance and cash holdings. Following Cole and McCullough (2006), reinsurance usage (REINSURANCE) is measured by the ratio of premiums ceded to the sum of direct premiums written and reinsurance assumed.

Catastrophe Risk: Insurers with a higher exposure to catastrophe risk have a higher demand for cash for precautionary reasons. Therefore, a positive relation is expected between cash holdings and catastrophe risk. Following Gron (1999), we measure insurers' exposure to catastrophe risk (CATASTROPHE) by the percentage of premiums that are written in property lines in the southern and eastern coastal areas.[49]

Diversification: Duchin (2010) finds that diversified firms hold less precautionary cash than focused firms because both the investment opportunities and the cash flows of diversified firms' divisions are not perfectly correlated. So, in our study, we control for insurers' diversification extent by including both their business lines diversification (LINES_DIV) and their geographic diversification (GEO_DIV). Following Berry-Stölzle et al., (2012), we use the complement of the Herfindahl index of net premiums written (NPW) across all lines of business to measure insurers' business line diversification.[50] This measure is calculated as follows,

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[49] Consistent with Gron (1999), the property lines include automobile physical damage, commercial multiple peril, earthquake, farmowners' multiple peril, fire and allied lines, homeowners' multiple peril, and inland marine. The southern and eastern coastal areas include the following states: Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Rhode Island, South Carolina, Texas, Virginia, and Washington, D.C.

[50] Net premiums written (NPW) represents premiums after consideration of the impact of reinsurance on direct premiums written. NPW more precisely captures the exposure an insurer has to a given line or market following reinsurance transactions.

$$LINES\_DIV_{i,t} = 1 - \sum_{j=1}^{24} \left(\frac{NPW_{i,j,t}}{NPW_t}\right)^2 \quad (8)$$

where $NPW_{i,j,t}$ denotes the net premiums written by insurer i in line $j = 1, \ldots, 24$ in year t, and $NPW_{i,t}$ denotes the total net premiums written by insurer i in a given year t.[51] Larger values of $LINES\_DIV_{i,t}$ represent greater levels of diversification. Following Liebenberg and Sommer (2008), we use the complement of the Herfindahl index of direct premiums written (DPW) across 58 states and territories as the geographic diversification measure.[52] Our measure of geographic diversification is calculated as follows,

$$GEO\_DIV_{i,t} = 1 - \sum_{k=1}^{58} \left(\frac{DPW_{i,k,t}}{DPW_{i,t}}\right)^2 \quad (9)$$

where $DPW_{i,k,t}$ denotes the direct premiums written by an insurer i in state $k = 1, \ldots, 58$ in year t, and $DPW_{i,t}$ denotes the total direct premiums written in a given year t.

Year, State, and Line Fixed Effects: Our data sample spans from 1999 to 2015. During this period, there are substantial fluctuations in both financial markets and insurance markets. For example, our sample includes the 2001 terrorist attacks, the 2005 losses from hurricanes Katrina, Rita, and Wilma, and the 2008-2009 financial crisis. Thus, we add year fixed effects to control for changes in cash holdings due to the changing conditions of financial markets and insurance markets. In addition, since the insurance industry is regulated at the state level, we include state fixed effects to control for state-specific differences in regulatory stringency.[53]

[51] Data necessary for the calculation of the $Lines\_DIV_{i,t}$ variable are obtained from the "Underwriting and Investment Exhibit (Part 1B – Premiums)" section of the NAIC annual statement, which allows for the inclusion of both the "reinsurance" and "international" lines that are included in the measure of diversification employed by Berry-Stölzle et al. (2012).

[52] Premiums written across states and territories is obtained from Schedule T of the NAIC Annual Statements. While insurers report direct and net premiums written at the business line level, insurers do not report net premiums written at the state/territorial level.

[53] As is discussed in Xie et al. (2017), although the U.S. insurance industry is highly regulated, there is no direct regulation of insurers' cash holdings. Instead, regulators impose requirements on insurers' liquidity, and cash holdings are an important component of insurers' liquid assets.

Finally, we control for an insurer's participation in different business lines by including line fixed effects.

Endogeneity

In our multivariate analysis, we first estimate our baseline model using an ordinary least squares (OLS) regression. However, prior literature suggests that market concentration is endogenous because market concentration might be jointly determined with firms' financial conditions (e.g., Bajtelsmit and Bouzouita, 1998; Uhde and Heimeshoff, 2009; Shim, 2017). As a consequence, the estimation of the OLS regression will be biased and inconsistent.

Following Shim (2017), we perform a two-stage least squares (2SLS) regression with instrumental variables to deal with the endogeneity problem.[54] According to Wooldridge (2002), successful instrumental variables should satisfy two conditions. The first condition is that the instrumental variables must be correlated with the endogenous explanatory variable. The second condition is that the instrumental variables must be uncorrelated with the error term in the explanatory equation. Shim (2017) proposes a set of potential candidates for the successful instrumental variables. Consistent with Shim (2017), our initial candidates include one-year industry growth, average firm size in the previous five years, five-year average growth rate of insurers' net premiums written, and lagged values of independent variables in Equation (1). Since we focus on insurers' state-line market segments and our measures of market concentration are insurer-year specific, we adopt a weighted measure for industry growth. Specifically, we first calculate the industry growth in each state-line market segment using direct premiums written and then weight the growth rates by the proportion of an insurer's business in

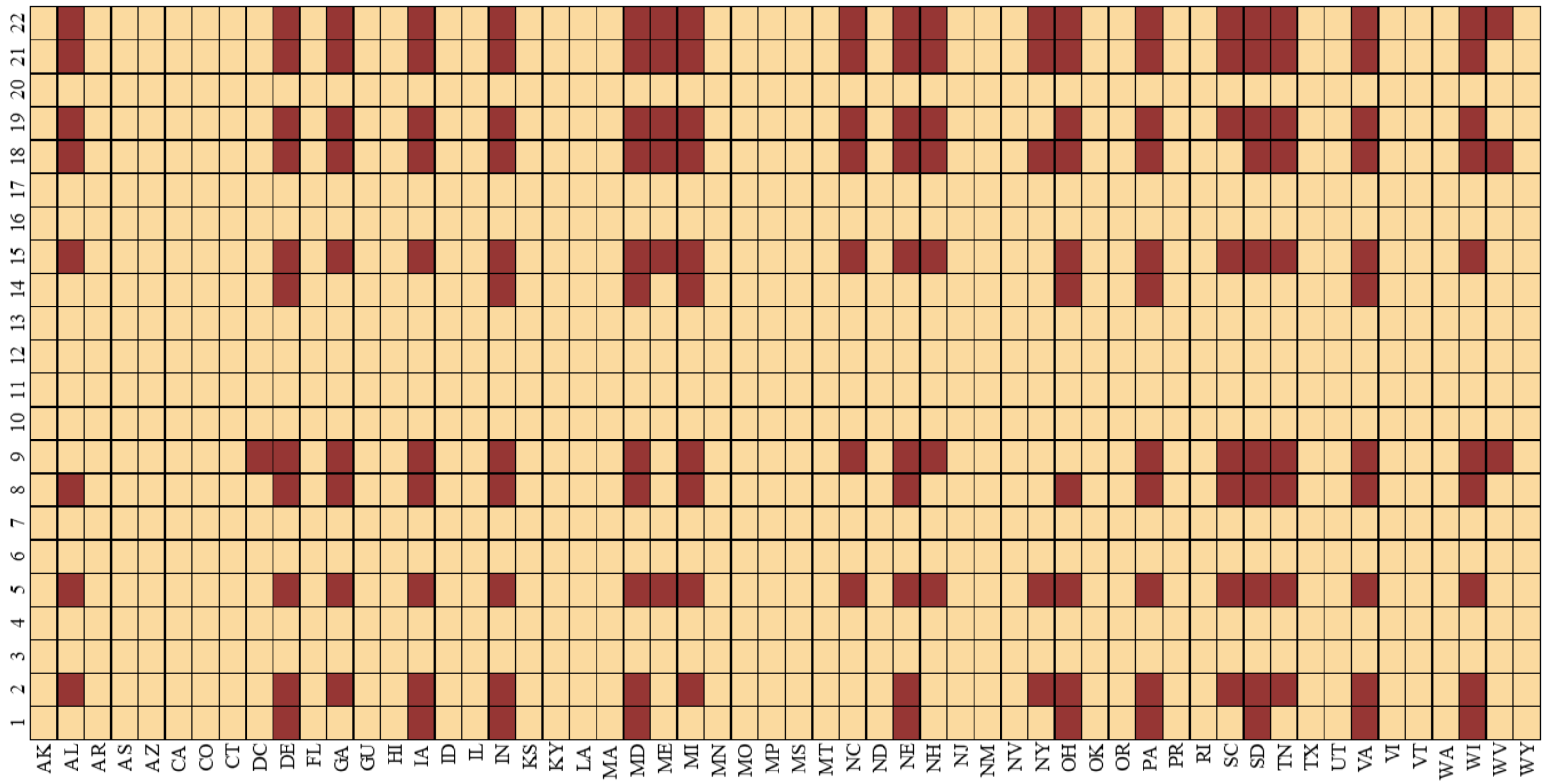
[54] The Hausman test rejects the null hypothesis of exogeneity and thus suggests a potential endogenous relation between cash holdings and market concentration.

each segment. To identify the successful instruments, we test instrument relevance by a Wald test and instrument validity by a Hansen's *J*-test of overidentifying restrictions. We find that the state-line weighted one-year industry growth and the average firm size in the previous five years satisfy the requirements of both relevancy and validity.

Following Campa and Kedia (2002), we also attempt to address the endogeneity problems using a firm fixed-effects regression. However, our market space weighted concentration measures do not have sufficient within-firm variation, hindering the applicability of the firm fixed-effects model.[55] Thus, we address the panel nature of our data by adjusting the standard errors for firm-level clustering.

[55] For example, the mean and the standard deviation of MS_WCONC (MS_WC4) for Allstate during our sample period (1999-2015) are 0.0870 and 0.0017 (0.4983 and 0.0046), respectively. The mean and the standard deviation of MS_WCONC (MS_WC4) for State Farm during our sample period are 0.0923 and 0.0010 (0.5078 and 0.0041), respectively.

Figure 1
Market Space of Donegal Insurance Group in 2015



This figure exhibits the market space of Donegal Insurance Group in 2015. The horizontal axis represents the U.S. states and territories. The vertical axis represents the following 22 unique lines of business: farmowners' multiple peril (1), homeowners' multiple peril (2), mortgage guaranty (3), ocean marine (4), inland marine (5), financial guaranty (6), medical professional liability (7), earthquake (8), workers' compensation (9), products liability (10), aircraft (11), fidelity (12), surety (13), burglary and theft (14), boiler and machinery (15), credit (16), other (17), fire and allied lines (18), commercial multiple peril (19), accident and health (20), other liability (21), and auto (22). Each dark box represents the presence of Donegal in the corresponding state-line market segment, and each light box represents the absence. Donegal is considered as present in a state-line market segment if it has positive direct premiums written in that segment and considered as absent if not.

DATA AND SAMPLE

We obtain an initial sample of U.S. property-liability insurance companies from the National Association of Insurance Commissioners (NAIC) InfoPro database for the years 1995 through 2015. Consistent with Shim (2017), we aggregate affiliated insurance companies [56] because insurers compete with each other at the group level rather than the individual firm level. Following Colquitt, Sommer, and Godwin (1999), we exclude insurers with non-positive assets, capital, net premiums written, or an organizational form other than stock or mutual. Following Hsu, Huang, and Lai (2015), we also eliminate insurers that report negative cash or negative invested assets. Our continuous variables are winsorized at the 1st percentile and the 99th percentile to avoid potential bias caused by outliers. Since we require data from the previous five years to calculate cash flow volatility, the final sample covers the period 1999 to 2015 and consists of a total of 11,225 firm-year observations (1,134 unique firms).

Table 1 presents variable descriptions and predicted signs for our independent variables and Table 2 reports summary statistics. The average cash holdings represent 19.07 percent of total invested assets in our sample while the minimum cash holdings are 0.44 percent and the maximum cash holdings is 100 percent. Our market space weighted concentration measure (MS_WCONC) has a mean of 9.33 percent with a minimum value of 3.17 percent and a maximum value of 40.90 percent. The alternative measure of market space weighted concentration (MS_WC4) has a mean of 47.20 percent with a minimum value of 25.59 percent

[56] To avoid double counting of assets when aggregating affiliate-level data, we net out investments in affiliates.

and a maximum value of 90.84 percent. In addition, the average insurer in our sample is approximately 44 years old, and roughly 7 percent of our sample consists of publicly-traded firms. Figure 2 and Figure 3 complement our descriptive statistics by showing the time series of industry-wide cash holdings and market concentration in the U.S. property-liability insurance industry. Figure 2 shows that cash holdings increased sharply from 1999 through 2003. The size of cash holdings in 2003 is almost three times as large as that in 1999. Following the 2008 financial crisis, cash holdings decreased until 2011. While the amount of cash holdings slightly increases following 2011, the percentage of cash holdings remains relatively constant. Figure 3 exhibits the industry-wide market concentration measured by the Herfindahl index and the four-firm concentration ratio in Panel A and Panel B, respectively. We find that similar to the time trend of cash holdings, market concentration increased significantly in the early 2000s and decreased following the financial crisis.

Table 1
Variables and Their Descriptions

Variable Name	Variable Description	Predicted Sign
Cash Holdings Measure:		
CASH	Cash holdings, as measured by the ratio of cash plus short-term investments to total invested assets.	
Concentration Measures:		
MS_WCONC	Market space weighted concentration, as measured by the weighted Herfindahl index of direct premiums written in an insurer's state-line market space.	+/-
MS_WC4	Market space weighted four-firm concentration ratio, as measured by the weighted proportion of direct premiums written by the largest four insurers in an insurer's state-line market space.	+/-
Control Variables:		
SIZE	Firm size, as measured by the natural logarithm of total net admitted assets.	-
FIN_STREN	Financial strength, as measured by a dummy variable that is equal to 1 if an insurer does not fail four or more IRIS ratios and 0 otherwise.	-
GROUP	Group status, as measured by a dummy variable that is equal to 1 for an affiliated insurer and 0 for an unaffiliated insurer.	-
VOL_CF	Volatility of cash flows, as measured by the standard deviation of net cash flows from operations over the previous five years.	+
DURATION	Duration of liabilities, as measured by the weighted average duration of liabilities in each line of an insurer. The information of duration for each line is obtained from Babbel and Klock (1994) and Cummins and Weiss (1991), and the average is used if the line is not reported in these two studies. The weights are based on insurers' unpaid losses and loss adjustment expenses.	-
STOCK	Organizational form, as measured by a dummy variable that is equal to 1 for a stock insurer and 0 for a mutual insurer.	+/-
LEVERAGE	Leverage, as measured by the ratio of an insurer's total liabilities to total assets.	+/-
INV_OPT	Investment opportunity, as measured by the average growth in total assets over previous three years.	+
NON_INV_AT	Non-invested assets, as measured by the ratio of an insurer's total non-invested assets to its total assets.	+
COM_STOCK	Common stock holdings, as measured by the ratio of common stock holdings to total invested assets.	-
AGE	Firm age, as measured by the natural logarithm of the difference between an insurer's age and 5 (Hsu, Huang, and Lai, 2015). For an insurance group, the age is based on its oldest affiliate (Berry-Stözle et al., 2012).	+
DIVIDEND	Dividend, as measured by a dummy variable that is equal to 1 for an insurer that pays a cash dividend to its stockholders or policyholders in a year and 0 otherwise.	-
PUBLIC	Public status, as measured by a dummy variable that is equal to 1 for a publicly-traded insurer and 0 for a private insurer.	+/-
REINSURANCE	Reinsurance ratio, as measured by the ratio of premiums ceded to the sum of direct premiums written and reinsurance assumed.	-
CATASTROPHE	Catastrophe risk, as measured by the percentage of direct	+

	premiums written that are in property lines in coastal areas.	
LINES_DIV	Business line diversification, as measured by the complement of the Herfindahl index of net premiums written across all business lines.	-
GEO_DIV	Geographic diversification, as measured by the complement of the Herfindahl index of direct premiums written across all U.S. states and territories	-

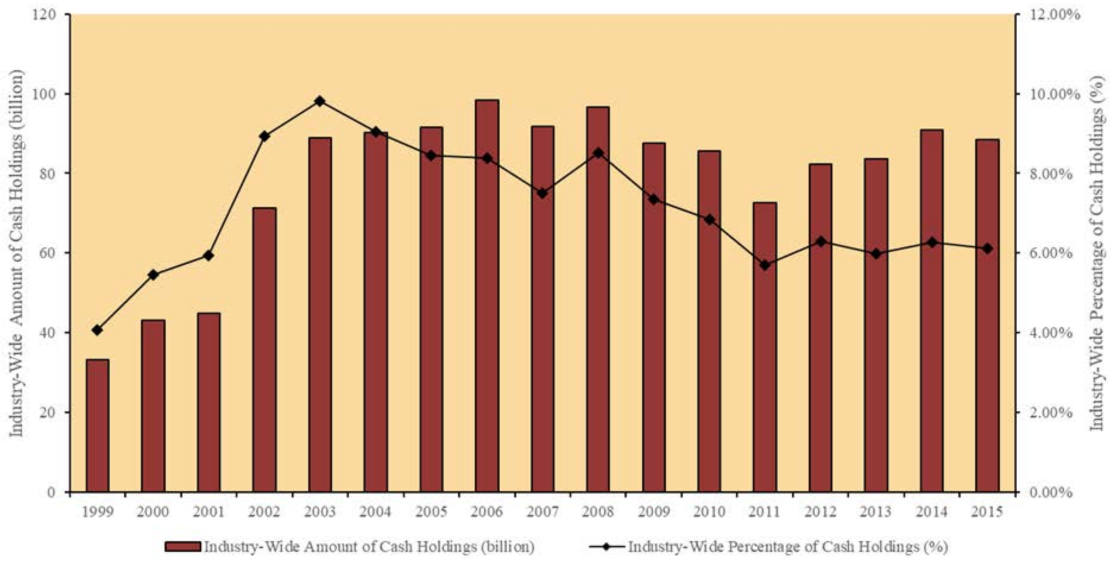
This table presents the variables, their descriptions, and predicted signs in the multivariate regressions.

Table 2
Summary Statistics

Variable Name	N	Mean	Median	Min	Max	Std. Dev.	1st Quartile	3rd Quartile
Dependent Variable:								
CASH	11,225	0.1907	0.0969	0.0044	1.0000	0.2332	0.0475	0.2267
Concentration Measures:								
MS_WCONC	11,225	0.0933	0.0786	0.0317	0.4090	0.0577	0.0636	0.0993
MS_WC4	11,225	0.4720	0.4593	0.2559	0.9084	0.1120	0.4006	0.5197
Control Variables:								
SIZE	11,225	18.1220	17.8477	13.2494	24.2135	2.3418	16.3713	19.6512
FIN_STREN	11,225	0.8697	1.0000	0.0000	1.0000	0.3367	1.0000	1.0000
GROUP	11,225	0.3263	0.0000	0.0000	1.0000	0.4689	0.0000	1.0000
VOL_CF	11,225	0.0589	0.0410	0.0056	0.3349	0.0555	0.0237	0.0731
DURATION	11,225	1.7453	1.5731	0.6400	4.9900	0.8504	1.4100	1.8035
STOCK	11,225	0.5294	1.0000	0.0000	1.0000	0.4992	0.0000	1.0000
LEVERAGE	11,225	0.5444	0.5802	0.0077	0.9178	0.1992	0.4293	0.6892
INV_OPT	11,225	0.0690	0.0519	-0.2269	0.7405	0.1222	0.0083	0.1054
NON_INV_AT	11,225	0.1494	0.1297	0.0000	0.6561	0.1146	0.0689	0.1977
COM_STOCK	11,225	0.1206	0.0742	-0.0011	0.7005	0.1461	0.0030	0.1732
AGE	11,225	3.6529	3.9318	0.0000	6.9470	1.2074	2.8904	4.6821
DIVIDEND	11,225	0.3919	0.0000	0.0000	1.0000	0.4882	0.0000	1.0000
PUBLIC	11,225	0.0728	0.0000	0.0000	1.0000	0.2598	0.0000	0.0000
REINSURANCE	11,225	0.2226	0.1556	0.0000	0.9197	0.2157	0.0621	0.3198
CATASTROPHE	11,225	0.1276	0.0000	0.0000	1.0000	0.2261	0.0000	0.1533
LINES_DIV	11,225	0.3585	0.4112	0.0000	0.8443	0.3052	0.0000	0.6514
GEO_DIV	11,225	0.3458	0.1594	0.0000	0.9576	0.3767	0.0000	0.7410

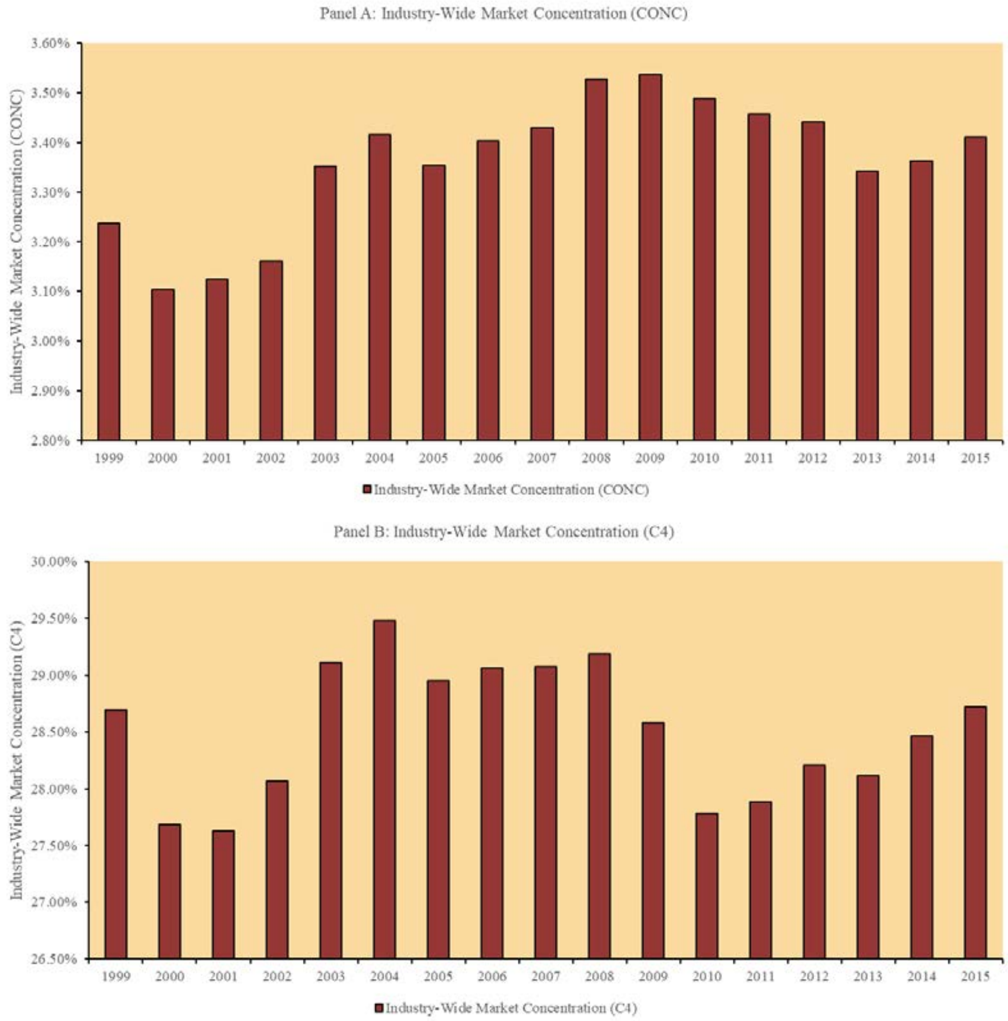
This table presents the summary statistics of the variables in the cash holdings regression. The variables are defined in Table 1. The data is obtained from the NAIC (National Association of Insurance Commissioners) InfoPro database for the years from 1995 through 2015. Affiliated insurers are aggregated at the group level and continuous variables are winsorized at the 1st and 99th percentiles. The final sample for the cash holdings regression covers the years from 1999 through 2015 and consists of 11,225 firm-year observations.

Figure 2
Industry-Wide Cash Holdings in the U.S. Property-Liability Insurance Industry



This figure exhibits the industry-wide cash holdings in the U.S. property-liability insurance industry from 1999 through 2015. The horizontal axis represents the year. The primary vertical axis (on the left) represents the industry-wide amount of cash holdings (billion), and the secondary vertical axis (on the right) represents the industry-wide percentage of cash holdings (%). The industry-wide percentage of cash holdings is calculated as the ratio of the industry's total cash plus short-term investments to the industry's total invested assets. The bar and the line depicts the industry-wide amount and the percentage of cash holdings, respectively.

Figure 3
Industry-Wide Market Concentration in the U.S. Property-Liability Insurance Industry



This figure exhibits the industry-wide market concentration in the U.S. property-liability insurance industry from 1999 through 2015. The horizontal axis represents the year. The vertical axis represents the industry-wide market concentration. The industry-wide market concentration is measured by the Herfindahl index (CONC) and the 4-firm concentration ratio (C4) in Panel A and Panel B, respectively.

UNIVARIATE ANALYSIS

Prior to testing our hypotheses using a multivariate approach, we first examine the relation between cash holdings and market concentration in a univariate setting. Table 3 compares cash holdings between insurers that are exposed to high market concentration and insurers that are exposed to low market concentration. Market concentration is measured by MS_WCONC and MS_WC4 in Panel A and Panel B, respectively. We classify market concentration as high if the market concentration is above the median and as low if the market concentration is below the median. We find that insurers exposed to high market concentration hold more cash than those exposed to low market concentration, and that the difference in cash holdings (both mean and median) is statistically significant. In Panel A, mean cash holdings of insurers that face high market concentration is 19.48 percent while insurers that face low market concentration have average cash holdings of 18.64 percent. These univariate results hold when we use the alternative measure of market concentration (MS_WC4) in Panel B. Overall, the univariate comparisons presented in Table 3 provide initial evidence of a positive relation between market concentration and cash holdings which is consistent with the predation risk theory.

Table 3
Univariate Comparison

Variable		High Concentration (1)	Low Concentration (2)	Difference (3) = (1) - (2)	p-value (4)	t-statistic (5)
Panel A: High Concentration > Median of MS_WCONC and Low Concentration < Median of MS_WCONC						
CASH	Mean	0.1949	0.1864	0.0085	0.05	1.93
	Median	0.0982	0.0957	0.0025	0.04	
	N	5,612	5,612			
Panel B: High Concentration > Median of MS_WC4 and Low Concentration < Median of MS_WC4						
CASH	Mean	0.2026	0.1787	0.0239	0.00	5.45
	Median	0.1014	0.0927	0.0086	0.00	
	N	5,612	5,612			

This table compares the cash holdings between insurers that are exposed to high market concentration and insurers that are exposed to low market concentration. The market concentration is measured by MS_WCONC and MS_WC4 in Panel A and Panel B, respectively. MS_WCONC and MS_WC4 are defined in Table 1. The market concentration is classified as high or low based on its median. The significance of differences in means is tested by a *t*-test. The significance of differences in medians is tested by a Wilcoxon rank-sum test.

MULTIVARIATE ANALYSIS

Table 4 presents results of multivariate regressions of cash holdings on market space concentration using both an ordinary least squares (OLS) and two-stage least squares (2SLS) approach. The first and the second columns in the table present the results when using MS_WCONC as the key independent variable, and the third and the fourth columns present the results when we use MS_WC4 as the key independent variable. The fifth column contains the results reported by Colquitt, Sommer, and Godwin (1999) for comparative purposes. We find that the coefficient on MS_WCONC is positive and statistically significant in both the OLS and the 2SLS regressions. Alternatively, when we use MS_WC4 as our market concentration measure, the coefficient is still positive and statistically significant in both regressions. The results suggest that increased market concentration is associated with greater insurer cash holdings. Similar to our findings in the univariate analysis, this result is consistent with the predation risk theory of cash holdings (Hypothesis 1).

The results presented in Table 4 are largely consistent with those of Colquitt, Sommer and Godwin (1999) (hereafter CSG) with only a few exceptions. First, the group status (GROUP) variable is positively related to cash holdings in our 2SLS models but is inversely related to cash holdings in the CSG (1999) study. Given that our study aggregates firms at the group level while their study does not, one potential explanation for this difference is that that even though the individual insurers in the group hold less cash because of the liquidity help from other affiliated insurers, the group, as a whole, needs to hold more cash to fulfill the demand of its members for liquidity.[57] Second, CSG (1999) find that the coefficients on investment opportunity (INV_OPT) and non-invested assets (NON_INV_AT) are not statistically significant. However, we find significant relations, and the signs of these two variables are consistent with the initial expectations stated in CSG (1999). Beyond the aforementioned differences, all other results presented in Table 4 are consistent with CSG (1999).

As a robustness check, we also follow Xie, et al. (2017) and use the natural logarithm of cash holdings as the dependent variable. The results are reported in the last four columns. We find that they are qualitatively similar to the results when the dependent variable is cash holdings.

[57] Similar to our results, Che and Liebenberg (2017) also provide some evidence that insurance groups have greater cash holdings relative to unaffiliated insurers.

Table 4
Effects of Market Concentration on Cash Holdings

Dependent Variable:	CASH					Ln(CASH)			
	OLS	2SLS	OLS	2SLS	CSG (1999)	OLS	2SLS	OLS	2SLS
INTERCEPT	1.0713***	1.0979***	1.0326***	0.9498***	0.5929***	2.3016***	2.4364***	2.1558***	1.7744***
	(0.0884)	(0.0911)	(0.0887)	(0.1040)	(0.0001)	(0.3412)	(0.3439)	(0.3389)	(0.3645)
MS_WCONC	0.2045*	0.5916*				0.7525*	2.7125***		
	(0.1064)	(0.3173)				(0.3947)	(0.7487)		
MS_WC4			0.1067*	0.4655*				0.4077*	2.0603***
			(0.0552)	(0.2478)				(0.2174)	(0.5913)
SIZE	-0.0461***	-0.0496***	-0.0455***	-0.0493***	-0.0189***	-0.2659***	-0.2832***	-0.2636***	-0.2813***
	(0.0050)	(0.0057)	(0.0049)	(0.0056)	(0.0001)	(0.0202)	(0.0215)	(0.0200)	(0.0216)
FIN_STREN	-0.0552***	-0.0542***	-0.0552***	-0.0532***	-0.0180***	-0.2344***	-0.2293***	-0.2341***	-0.2249***
	(0.0097)	(0.0098)	(0.0097)	(0.0100)	(0.0001)	(0.0413)	(0.0419)	(0.0413)	(0.0427)
GROUP	0.0194	0.0210*	0.0190	0.0204*	-0.0432***	0.1197*	0.1278*	0.1181*	0.1247*
	(0.0120)	(0.0121)	(0.0120)	(0.0123)	(0.0001)	(0.0668)	(0.0673)	(0.0668)	(0.0681)
VOL_CF	0.4731***	0.4489***	0.4767***	0.4459***	0.1333***	2.3565***	2.2341***	2.3685***	2.2266***
	(0.0881)	(0.0895)	(0.0881)	(0.0903)	(0.0351)	(0.3268)	(0.3345)	(0.3267)	(0.3389)
DURATION	-0.0172**	-0.0256**	-0.0177**	-0.0344**	-0.0213***	-0.0513	-0.0939**	-0.0540	-0.1311***
	(0.0086)	(0.0106)	(0.0087)	(0.0142)	(0.0001)	(0.0401)	(0.0404)	(0.0405)	(0.0459)
STOCK	0.0225*	0.0198*	0.0227*	0.0185	0.0558***	0.1475***	0.1340**	0.1480***	0.1288**
	(0.0118)	(0.0120)	(0.0118)	(0.0123)	(0.0001)	(0.0531)	(0.0531)	(0.0532)	(0.0543)
LEVERAGE	-0.1455***	-0.1390***	-0.1475***	-0.1425***	-0.0356*	-0.3852**	-0.3522**	-0.3922**	-0.3692**
	(0.0394)	(0.0396)	(0.0395)	(0.0402)	(0.0888)	(0.1639)	(0.1660)	(0.1642)	(0.1695)
INV_OPT	0.1088***	0.1157***	0.1077***	0.1161***	0.0054	0.6286***	0.6635***	0.6247***	0.6638***
	(0.0307)	(0.0314)	(0.0307)	(0.0315)	(0.5126)	(0.1265)	(0.1284)	(0.1265)	(0.1287)
NON_INV_AT	0.1018*	0.1096*	0.1004*	0.1096*	0.0229	0.6479***	0.6872***	0.6432***	0.6853***
	(0.0556)	(0.0560)	(0.0555)	(0.0563)	(0.4459)	(0.2016)	(0.2039)	(0.2014)	(0.2054)
COM_STOCK	-0.2861***	-0.2889***	-0.2865***	-0.2929***	-0.1753***	-0.9742***	-0.9884***	-0.9759***	-1.0052***
	(0.0349)	(0.0356)	(0.0349)	(0.0367)	(0.0001)	(0.1631)	(0.1649)	(0.1631)	(0.1673)
AGE	0.0041	0.0038	0.0037	0.0022		0.0061	0.0049	0.0049	-0.0020
	(0.0063)	(0.0063)	(0.0064)	(0.0065)		(0.0254)	(0.0256)	(0.0255)	(0.0263)
DIVIDEND	0.0069	0.0075	0.0073	0.0098		-0.0097	-0.0066	-0.0081	0.0033
	(0.0096)	(0.0096)	(0.0096)	(0.0098)		(0.0472)	(0.0472)	(0.0472)	(0.0473)
PUBLIC	0.0048	0.0108	0.0044	0.0139		-0.0508	-0.0204	-0.0517	-0.0083
	(0.0125)	(0.0136)	(0.0124)	(0.0143)		(0.0868)	(0.0888)	(0.0865)	(0.0902)
REINSURANCE	0.0623**	0.0634**	0.0644**	0.0731**		0.4299***	0.4353***	0.4378***	0.4783***
	(0.0293)	(0.0292)	(0.0292)	(0.0298)		(0.1098)	(0.1096)	(0.1095)	(0.1116)

CATASTROPHE	0.0496	0.0484	0.0481	0.0412		0.1186	0.1126	0.1130	0.0810
	(0.0301)	(0.0301)	(0.0302)	(0.0308)		(0.1225)	(0.1225)	(0.1227)	(0.1244)
LINES_DIV	-0.0986***	-0.1030***	-0.0977***	-0.1025***		-0.3685**	-0.3907***	-0.3654**	-0.3875***
	(0.0292)	(0.0301)	(0.0292)	(0.0307)		(0.1439)	(0.1457)	(0.1438)	(0.1476)
GEO_DIV	-0.0507**	-0.0447**	-0.0506**	-0.0397*		-0.1218	-0.0914	-0.1210	-0.0705
	(0.0207)	(0.0214)	(0.0206)	(0.0225)		(0.1078)	(0.1100)	(0.1076)	(0.1128)
Wald Test Statistics		5.6110***		3.7270**			5.6110***		3.7270**
Hansen's J Statistics		0.5421		0.5957			0.8680		0.8353
Year Fixed Effects	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Line Fixed Effects	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Adjusted R^2	0.3807	0.3745	0.3807	0.3616	0.2224	0.4105	0.4041	0.4106	0.3943
Observations	11,225	11,225	11,225	11,225		11,225	11,225	11,225	11,225

This table presents the multivariate regressions of cash holdings on market concentration. The dependent variables are cash holdings (CASH) and its natural logarithm (Ln(CASH)). The variables are defined in Table 1. OLS is an ordinary least squares regression. 2SLS is a two-stage least squares regression. Instruments include state-line weighted one-year industry growth and average firm size in the previous five years. Standard errors (in parentheses) are corrected for clustering at the insurer level. The column labeled "CGS (1999)" presents the coefficients and p-values (in parentheses) reported by Colquitt, Sommer, and Godwin (1999). *, **, and *** denote statistical significance at 10%, 5%, and 1% levels respectively.

FUTURE GROWTH

In the previous section, we found that insurers tend to hold more cash if they underwrite in more concentrated markets. However, it is still unclear whether the excess cash holdings are used to hedge predation risk. By definition, predation risk refers to "the risk of underinvestment leading to a loss of investment opportunities and market share to product market rivals" (Haushalter, Klasa, and Maxwell, 2007). Hsu, Huang, and Lai (2015) provide an approach to examine whether a higher level of cash holdings is used to prevent the underinvestment problem. We follow their approach and provide evidence from the perspective of insurers' future growth.

Following Hsu, Huang, and Lai (2015), we employ the average growth rate of direct premiums written for the following three years as the proxy for future growth and use the decomposed excess cash holdings interacted with market concentration as the key variables to test whether a higher level of cash holdings is used to hedge predation risk. Excess cash holdings (EX_CASH) are defined as the difference between the actual cash holdings and the target cash holdings. The target cash holdings are estimated by either the regression model specified by CSG (1999) with year dummies or a Fama-MacBeth model with variables specified in the CSG.[58] Following Hsu, Huang, and Lai (2015), we call the excess cash holdings "positive excess cash

[58] The Fama-MacBeth model treats each year as an independent cross-section and gives the average of the time series of coefficients from annual cross-sectional regressions. We also check the robustness of our results by using an alternative specification of variables in calculating the target cash holdings. Specifically, we use the variables in our full specification (excluding the market concentration measures) in Table 4 to estimate the target level of cash holdings. The target cash holdings are estimated by either the full specification model with year dummies or the Fama-MacBeth model with variables specified in the full specification model. We reproduce our results in our study. In unreported tables, we find that our results are robust to this alternative estimation of the target cash holdings.

holdings" if the excess cash holdings are positive and "negative excess cash holdings" if the excess cash holdings are negative. The method used to calculate the decomposed variables is consistent with Morck, Shleifer, and Vishny (1988) and Wruck (1989). Specifically, we create two excess cash holdings variables, where the positive (negative) excess cash holdings variable is equal to a firm's excess cash holdings if cash holdings are greater than or equal to (less than) zero and otherwise the variable is equal to zero. Following Hsu, Huang, and Lai (2015), we control for firm size (SIZE), firm age (AGE), line-of-business diversification (LINES_DIV), and geographic diversification (GEO_DIV) in our models.

Table 5 presents the multivariate regressions of future growth on market space concentration. It shows that the coefficient on the interaction term between negative excess cash and market concentration ($EX\_CASH_{(negative)}$×MS_WCONC or $EX\_CASH_{(negative)}$×MS_WC4) is positive and significant, while the coefficient on the interaction term between positive excess cash and market concentration ($EX\_CASH_{(positive)}$×MS_WCONC or $EX\_CASH_{(positive)}$×MS_WC4) is statistically insignificant. These results provide evidence in support of H1.1 (Predation Risk Hypothesis). Specifically, an increase in cash holdings leads to faster future growth when market concentration is higher. We note that this relation is statistically significant only when cash holdings are below the target level and that the significance vanishes when cash holdings are above the target level, implying that holding too much cash is not optimal. Similar results are also obtained when the Fama-MacBeth model is used to estimate the target cash holdings.

Table 5
Effects of Market Concentration and Excess Cash Holdings on Future Growth

Dependent Variable: DPW_GROWTH				
Target Cash Holdings Model:	CSG Model with Year Dummies		Fama-MacBeth Model with CSG Variables	
	OLS	OLS	OLS	OLS
INTERCEPT	0.2933***	0.3033***	0.2918***	0.3008***
	(0.0541)	(0.0536)	(0.0542)	(0.0540)
EX_CASH	-0.0432	-0.1213	-0.0410	-0.1145
	(0.0362)	(0.0799)	(0.0365)	(0.0805)
$EX\_CASH_{(positive)}$×MS_WCONC	0.1648		0.1683	
	(0.3998)		(0.4028)	
$EX\_CASH_{(negative)}$×MS_WCONC	1.4279**		1.3353**	
	(0.5827)		(0.5958)	
$EX\_CASH_{(positive)}$×MS_WC4		0.1852		0.1781
		(0.1709)		(0.1712)
$EX\_CASH_{(negative)}$×MS_WC4		0.4562**		0.4247**
		(0.2005)		(0.2039)
MS_WCONC	-0.0328		-0.0352	
	(0.0724)		(0.0713)	
MS_WC4		-0.0112		-0.0114
		(0.0390)		(0.0388)
SIZE	-0.0061*	-0.0067**	-0.0060*	-0.0065**
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
AGE	-0.0098**	-0.0095**	-0.0098**	-0.0095**
	(0.0046)	(0.0047)	(0.0046)	(0.0047)
LINES_DIV	0.0208	0.0185	0.0211	0.0188
	(0.0251)	(0.0251)	(0.0251)	(0.0251)
GEO_DIV	0.0310	0.0307	0.0307	0.0305
	(0.0202)	(0.0200)	(0.0202)	(0.0200)
Year Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Line Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.0800	0.0796	0.0799	0.0793
Observations	8,192	8,192	8,192	8,192

This table presents the multivariate regressions of future growth on market concentration. The dependent variable is the future growth (DPW_GROWTH), calculated as the average growth rate of direct premiums written for the following three years. The excess cash holdings (EX_CASH) are calculated as the difference between the actual cash holdings and the target cash holdings. The target cash holdings are estimated by either the regression model specified by Colquitt, Sommer, and Godwin (1999) (CSG) with year dummies or the Fama-MacBeth model with variables specified in the CSG. $EX\_CASH_{(positive)}$= 0 if EX_CASH < 0; $EX\_CASH_{(positive)}$= EX_CASH if EX_CASH >= 0. $EX\_CASH_{(negative)}$= EX_CASH if EX_CASH < 0; $EX\_CASH_{(negative)}$= 0 if EX_CASH >= 0. All remaining variables are defined in Table 1. OLS is an ordinary least squares regression. Standard errors (in parentheses) are corrected for clustering at the insurer level. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels respectively.

CONCLUSION

The predation risk theory and the financial constraint-based theory yield competing predictions on the relation between market concentration and corporate cash holdings policy. Taking advantage of the detailed data reported by firms in the U.S. property-liability insurance industry, we investigate the relation between cash holdings policy and market concentration. In this study, we propose a measure for market concentration, *market space weighted concentration*, which we contend more accurately reflects an insurer's state-line market space. Through our empirical analysis, we find that market concentration is positively related to cash holdings, which supports the predation risk theory. Furthermore, we show that an increase in cash holdings leads to insurers' faster future growth when market concentration is higher, which provides further support for predation risk theory. While the results indicate that the marginal benefit of cash holdings increases with market concentration, we find that the effect only exists when cash holdings are below the target level, which implies that holding too much cash is not optimal - even in a more concentrated market.

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Education

M.S. in Finance, Syracuse University, Syracuse, NY, U.S., May 2014

B.S. in Economics, Xi'an Jiaotong University, Xi'an, Shaanxi, China, July 2012

Refereed Publications

- Che, X., Liebenberg, A.P., 2017. Effects of Business Diversification on Asset Risk-Taking: Evidence from the U.S. Property-Liability Insurance Industry. Journal of Banking and Finance 77, 122-136.
- Che, X., Liebenberg, A.P., Liebenberg, I.A., Morris, B.C., 2017. The Effect of Growth Opportunities on the Market Reaction to Dividend Cuts: Evidence from the 2008 Financial Crisis. Review of Quantitative Finance and Accounting (Forthcoming).
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- Che, X., Van Ness, B.F., Van Ness, R.A., 2016. The Market for Small-Cap Stocks (NYSE MKT). Journal of Trading 11, 81-95.

Other Publications

- Che, X., Liebenberg, A.P., 2016. Underwriting Performance of Leading Insurers in Mississippi. Mississippi Agent 36, 34-46.

Refereed Presentations

- Portfolio Choice: Familiarity, Hedging, and Industry Bias (with Andre P. Liebenberg and Andrew A. Lynch), Financial Management Association (FMA) Annual Meeting, San Diego, CA, October 2018 (Scheduled).
- Portfolio Choice: Familiarity, Hedging, and Industry Bias (with Andre P. Liebenberg and Andrew A. Lynch), Southern Risk and Insurance Association (SRIA) Annual Meeting, Nashville, TN, November 2017.
- Effects of Market Concentration on Cash Holdings: Empirical Evidence from the U.S. Property-Liability Insurance Industry (with Andre P. Liebenberg and Stephen G. Fier), American Risk and Insurance Association (ARIA) Annual Meeting, Toronto, Canada, August 2017.
- Effects of Market Concentration on Cash Holdings: Empirical Evidence from the U.S. Property-Liability Insurance Industry (with Andre P. Liebenberg and Stephen G. Fier), University of Georgia Ph.D. Student Research Symposium, Athens, GA, February 2017.
- Effects of Business Diversification on Asset Risk-Taking: Evidence from the U.S. Property-Liability Insurance Industry (with Andre P. Liebenberg), American Risk and Insurance Association (ARIA) Annual Meeting, Boston, MA, August 2016.
- Effects of Business Diversification on Asset Risk-Taking: Evidence from the U.S. Property-Liability Insurance Industry (with Andre P. Liebenberg), Eastern Finance Association (EFA) Annual Meeting, Baltimore, MD, April 2016.
- Decomposing the Diversification Effect in the U.S. Property-Liability Insurance Industry (with Andre P. Liebenberg, Ivonne A. Liebenberg, and Lawrence S. Powell), Midwest Finance Association (MFA) Annual Meeting, Atlanta, GA, March 2016.

- Effects of Business Diversification on Asset Risk-Taking: Evidence from the U.S. Property-Liability Insurance Industry (with Andre P. Liebenberg), Midwest Finance Association (MFA) Annual Meeting, Atlanta, GA, March 2016.
- Effects of Business Diversification on Asset Risk-Taking: Evidence from the U.S. Property-Liability Insurance Industry (with Andre P. Liebenberg), Southern Risk and Insurance Association (SRIA) Annual Meeting, New Orleans, LA, November 2015.

Courses Taught

- FIN 331 Business Finance
- FIN 341 Risk and Insurance

Awards and Scholarships

- Elizabeth A. Kocur Memorial Scholarship, Griffith Insurance Education Foundation, 2017
- Whitman Merit Scholarship, Syracuse University, 2012
- Student Award of Excellence, Xi'an Jiaotong University, 2011
- Siyuan Scholarship, Xi'an Jiaotong University, 2009
- Student Award of Excellence, Xi'an Jiaotong University, 2009

Certificates

- CFA Level I, 2014
- FRM Part I, 2014
- SAS Certified Advanced Programmer, 2014

- SAS Certified Base Programmer, 2014
- Bloomberg Essentials Training Program Certificates, 2013