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Portfolio Choice: Familiarity, Hedging, and Industry Bias

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Abstract

Investors may underdiversify their portfolios by overweighting securities in which they perceive an informational advantage or by underweighting securities to hedge risks outside the portfolio. We investigate underdiversification in institutional portfolio construction by examining the under/overweighting of industries in U.S. property–liability (PL) insurers' equity portfolios. We find that PL insurers underweight both their own industry and highly correlated industries in their portfolios. This underweighting is larger for PL insurers exposed to higher underwriting risk. Although PL insurers have an informational advantage in investing in their peers, their underwriting risk drives them to underweight stocks in their industry.

I. Introduction

Modern portfolio theory contends that portfolios should be constructed to remove as much idiosyncratic risk as possible (see, e.g., Markowitz (1952), Sharpe (1964)). However, a vast literature documents underdiversification in equity portfolios (see, e.g., 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), and Von Gaudecker (2015)). Whether actually informed or uninformed,[1] underdiversified investors may be

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[1]For informed trading, see, for example, Kacperczyk, Sialm, and Zheng (2005), Ivković, Sialm, and Weisbenner (2008), and Van Nieuwerburgh and Veldkamp (2010). For uninformed trading, see, for example, Goetzmann and Kumar (2008), Huang, Sialm, and Zhang (2011), and Anderson (2013).

attempting to profit from asset allocation and security selection ability (Brown, Garlappi, and Tiu (2010)). For instance, an investor with perceived private information about a specific industry may overweight his allocation to securities in that industry to increase expected returns (Van Nieuwerburgh and Veldcamp (2009), Døskeland and Hvide (2011)). Conversely, an investor with nonfinancial income tied to a specific industry may underweight her allocation to equities in that industry, or related industries, to construct an appropriately diversified total portfolio (Massa and Simonov (2006)). These two incentives for underdiversification in equity portfolios are generally referred to as familiarity and hedging, respectively.

In this article, we examine industry bias, the choice to bias a portfolio toward (familiarity) or away from (hedging) specific industries, by studying investors that possess both private information and nonfinancial income: insurance companies. We analyze U.S. property–liability (PL) insurers' equity portfolios from 2001 through 2015 and find that PL insurers underweight PL insurance stocks in their portfolio despite earning abnormal returns when trading in their peers. Although PL insurers appear informed in their intraindustry equity trades, hedging nonfinancial income risk appears to dominate in their portfolio allocation decision. This hedging behavior is evident across their entire equity portfolio. PL insurers underweight industries the higher their correlation with the PL insurance industry. Additionally, consistent with this hedging explanation, we find that the extent of insurers' bias away from the PL insurance industry, and related industries, is positively related to their nonfinancial income risk (underwriting risk).

Massa and Simonov (2006) and Døskeland and Hvide (2011) examine industry bias in individual investor portfolios in Sweden and Norway, respectively.[2] Both papers find that individuals tilt their portfolios positively toward industries in which they are employed. However, they obtain conflicting results on the information content of the bias. Massa and Simonov find that the sensitivity of investors to familiarity differs with the degree of informativeness and decreases following familiarity shocks (unemployment and change of profession), suggesting that informed familiarity with their industry of employment is driving the positive industry bias. Døskeland and Hvide find negative (but insignificant) abnormal returns to same-industry investments, concluding that the positive industry bias is behavioral in nature.

Although the literature on individual portfolio allocation does not find evidence favoring hedging, the hedging motive for insurers, and other institutions, differs from individual investors, whose hedging is motivated by risk aversion. For widely held corporations, risk aversion is not a value-maximizing reason to hedge because their shareholders are able to costlessly eliminate idiosyncratic risk by holding diversified equity portfolios (e.g., Smith and Stulz (1985)). In the classic Modigliani and Miller (1958) model, diversified investors operate in complete and frictionless markets and corporate hedging is not value relevant because investors

[2]Massa and Simonov (2006) use data that cover detailed information on individual Swedish investors' holdings and their different sources of income, demographics, and family characteristics. Døskeland and Hvide (2011) employ data that cover the common stock holdings and transactions of all Norwegian individual investors at the Oslo Stock Exchange and supplement these investment data with information on sociodemographic characteristics of each investor obtained from the government statistical agency.

are able to alter their portfolios to offset changes to corporate hedging policy. However, the existence of market imperfections (such as financial distress costs, agency costs, and taxes) creates opportunities for hedging to increase net cash flows (e.g., Stulz (1984), Smith and Stulz (1985), and MacMinn (1987)). Furthermore, corporate hedging can maximize value by reducing the underinvestment problem (Bessembinder (1991), Froot, Scharfstein, and Stein (1993)). In addition to these general value-increasing hedging motives, theory suggests that derivatives hedging creates value for insurance companies because their customers are unusually sensitive to credit risk (Merton and Perold (1993)) and they face unique regulatory costs related to financial distress (Cummins, Phillips, and Smith (2001)).

Insurance company equity portfolios are a logical empirical setting to examine the hedging and familiarity aspects of industry bias. Insurance companies possess a deep understanding of the operations and profitability of an insurance business and continually collect private information about the current state of the insurance industry as they rate policies and pay claims. Of all investors, they should have the most private information concerning insurance stocks. They also have measurable exposure to nonfinancial income risk in the insurance industry, through gains or losses in underwriting. A complete examination of industry bias requires potentially informed investors and their nonfinancial income, both of which are difficult to measure in many investors.[3]

Nonfinancial income risk is a nontrivial concern for many institutional and individual investors beyond insurers. Pension funds, required to generate returns to meet the gap between firm contributions and distributions, allocate portfolio assets based in part on current and anticipated firm performance (Sharpe (1976), Bergstresser, Desai, and Rauh (2006)). Given that Americans held $12.7 trillion in equities in defined benefit and contribution retirement accounts in 2017,[4] identification of a relation between asset allocation and nonfinancial income in U.S. portfolios is economically meaningful. Similarly, university endowments exist as one of multiple sources of income for their institutions (tuition and, in the case of public institutions, state appropriations being the other two main sources). The construction of these endowment portfolios is conditional on the riskiness of the institution's nonfinancial income (Black (1976), Merton (1993), and Brown, Dimmock, Kang, and Weisbenner (2014)). However, of the institutional and individual investors concerned with nonfinancial income risk in the United States, only insurance companies are required to publicly disclose both nonfinancial income and disaggregated portfolio holdings.

The regulatory reporting requirements for insurance firms provide rich financial and investment data that allow us to examine both the hedging and familiarity incentives for industry bias. All licensed insurers file annual statutory statements

[3]Individuals examined in Massa and Simonov (2006) and Døskeland and Hvide (2011) may infer knowledge of private information of the industry in which they are employed but are arguably exposed to low levels of nonfinancial income risk, which is relatively difficult to observe. Similarly, although pension (Blake, Lehmann, and Timmermann (1999)) and endowment (Brown et al. (2010)) funds are exposed to nonfinancial income risk, the measurement of that risk is uncertain.

[4]This number is according to the 2018 Global Pension Assets Study by Willis Towers Watson (https://www.thinkingaheadinstitute.org/en/Library/Public/Research-and-Ideas/2019/02/Global-Pension-Asset-Survey-2019).

with regulators that provide detailed financial information on assets, liabilities, income, and such, by which we are able to quantify their nonfinancial income risk and measure other firm characteristics. A particularly unique reporting requirement for insurers is the detailed and disaggregated disclosure of all investments, including common stock holdings and daily transactions.[5] Using these data, we can accurately measure deviations in PL insurers' equity portfolios from the market portfolio.[6]

We find that the mean PL insurer underweights PL stocks by 20.81% relative to PL market weights. More striking is that the median PL insurer holds no PL stocks, choosing to forgo exposure to a 2.73% piece of the public equity market. This underweighting is conditional on underwriting risk. An increase in underwriting risk results in additional underweighting, suggesting that the underweighting of same-industry equities is, in part, driven by a hedging motivation. This hedging behavior extends to all equities. PL insurers underweight industries the higher their correlation with the PL industry, and the magnitude of this underweighting is larger for insurers with high underwriting risk.[7]

Interestingly, although PL insurers underweight equities in their own industry, we find evidence of informed investment in same-industry stocks. When PL insurers hold equity in other PL insurers, they prefer similar firms. They are more likely to invest in PL insurers whose returns are correlated with theirs and whose business overlaps with their business, either geographically or in type of insurance lines offered. However, this preference for similar firms is significantly reduced for PL insurers with high underwriting risk, suggesting that hedging concerns can dominate familiarity when sufficiently large. More importantly, when PL insurers choose to trade PL equities, they appear to be informed. Buy-minus-sell calendar-time returns reveal an annualized 4-factor alpha of as much as 6.78% when PL insurers buy or sell stocks in their own industry. This informed trading does not extend to trading outside the PL insurance industry. Overall, although PL insurers are familiar with their industry and trade informatively, hedging nonfinancial risk dominates the choice in allocating assets to PL insurer stocks.

Our article contributes to the literature in two ways. First, we find empirical evidence that hedging nonfinancial risk plays an important role in shaping industry bias. This implies that investors do not make investment decisions in silos, but instead use a coordinated diversification approach that takes nonfinancial income risk into account. To our knowledge, our article is the first to provide clear evidence of this hedging incentive and highlights the influence of nonfinancial income in investment portfolio allocation. Second, we find support for the information

[5]Although the largest asset class held by insurers is bonds, we do not examine industry bias in their bond portfolios. Insurers are subject to risk-based capital requirements that have no expected effect on stock portfolio allocation but that have been shown to affect the choice of bond investments. For more on this issue, see Ellul, Jotikasthira, and Lundblad (2011) and Becker and Ivashina (2015).

[6]We study PL insurers rather than other regulated financial institutions that also earn nonfinancial income because PL insurers have substantial investments in common stocks. According to the 2017 Insurance Fact Book prepared by the Insurance Information Institute, PL insurers' common stock portfolio ($326.2 billion) represents 21.30% of their total investments ($1.5 trillion) in 2015. The 2017 Insurance Fact Book can be found at http://www.iii.org/publications/insurance-fact-book-2017.

[7]Although short sales would be an ideal venue to study the hedging question, we do not consider them because insurers are generally prohibited from short selling via state laws that regulate insurer solvency (Molk and Partnoy (2019)).

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advantage of investors when investing in their own industry. This adds to a growing body of work that demonstrates the ability to generate abnormal returns by institutional investors (see, e.g., Kacperczyk et al. (2005), Puckett and Yan (2011)) and identifies an important source of information used by these investors. Given that the literature on individuals fails to discover hedging behavior or abnormal returns from same-industry investments, our article also provides support for the view that institutional investors are more sophisticated than individual investors.

II. Hypotheses

One of the core motivations of portfolio construction is diversification, where allocating a portfolio across multiple risky assets that are not perfectly correlated maintains expected returns while reducing risk. The optimal diversification in an equity portfolio is generally achieved by holding the market portfolio (see, e.g., Black (1976)). However, including an underwriting business in that portfolio, a nonfinancial risky asset outside the equity market, alters the optimally diversified allocation across equities for an insurer. Diversification of an insurer's total portfolio, the summation of its financial and nonfinancial assets, necessitates underweighting (overweighting) equities with high (low) correlations with its nonfinancial income relative to the market portfolio. This leads to our first hypothesis:

Hypothesis 1 (Hedging). PL insurers tilt their equity portfolios away from correlated stocks.

As correlation is continuous, this results in greater underweighting of stocks the stronger their relation to the PL insurance industry. This hedging behavior is expected to manifest itself in multiple ways. PL insurers could underweight the industry most correlated with the PL industry: the PL industry itself. Additionally, they could underweight industries that have relatively high return correlations with the PL industry. Or they could underweight other PL insurers with similar businesses (either high return correlations or overlapping insurance businesses).

The hedging-based incentive to deviate from the market portfolio stems entirely from the riskiness of the insurers' underwriting business. As the riskiness of their nonfinancial income increases, the incentive to underweight correlated stocks increases. Our second hypothesis is therefore as follows:

Hypothesis 2. PL insurers' equity portfolio tilt away from correlated stocks is exacerbated by their underwriting risk.

Insurers may deviate from the market portfolio not to hedge, but instead to capitalize on a perceived information advantage. This familiarity with specific securities may be derived from many sources: geographic proximity (Coval and Moskowitz (1999), Huberman (2001)), professional relation (Massa and Simonov (2006), Døskeland and Hvide (2011)), language and cultural similarity (Hau (2001)), or even simply investor awareness of the firm (Merton (1987), Frieder and Subrahmanyam (2005)). These studies generally find evidence that investors prefer to hold familiar stocks. For instance, Døskeland and Hvide (2011) examine portfolio allocation of Norwegian individual investors to specific industries relative to the market portfolio. They find that these investors overweight industries in which the individuals have work experience. This leads to our third hypothesis:

Hypothesis 3 (Familiarity). PL insurers tilt their equity portfolios toward familiar stocks.

There are several potential sources of familiarity for PL insurers. Given their expertise in underwriting PL insurance contracts, they should possess a deep familiarity with other PL insurers. There are ample opportunities for PL insurers to learn about their peers. For example, insurers often participate with others when insuring large commercial risks and many large insurers share (via reinsurance) in risks that have been underwritten by peer insurers. Additionally, the local bias literature implies that they should be more familiar with PL insurers who operate in similar geographic areas (states) or underwrite similar lines of business (e.g., workers' compensation, products liability, homeowners).

This familiarity may or may not lead to informed investing. Uninformed familiarity results in deviating from the market portfolio while failing to increase expected returns (Benartzi (2001), Pool, Stoffman, and Yonker (2012)). However, if familiarity generates an informational advantage, it should result in abnormal returns to trades made in familiar stocks (Coval and Moskowitz (1999), Massa and Simonov (2006), and Bernile, Kumar, and Sulaeman (2015), and Choi, Fedenia, Skiba, and Sokolyk (2017)). Our fourth hypothesis is as follows:

H4. PL insurers earn positive abnormal returns on their investments in familiar equities.

III. Data and Sample

We obtain the common stock holdings and transactions (i.e., buys and sells) data of PL insurers from the National Association of Insurance Commissioners (NAIC) InfoPro database for 2001–2015.[8] Schedule D (Parts 2–5) of PL insurers' annual statutory statements reports year-end stock holdings as well as intra-year transactions that are recorded on the date of each trade.[9] We delete stock holdings and trades with nonpositive number of shares or value. We aggregate stock-specific data for each insurer on each portfolio date (i.e., year-end) or transaction date. Daily stock information is obtained from the Center for Research in Security Prices (CRSP) database and merged with our stock holdings and transactions data.

[8]We choose 2001 as our starting year because before 2001, the transaction dates are recorded as "VARIOUS" in Schedule D of insurers' statutory statements if a stock is traded on multiple dates. Therefore, we are unable to identify the transaction dates for these stocks, which are needed by our transactions-based calendar-time portfolios. Furthermore, we do not include holdings or trades in stock of insurers that are affiliated (usually in terms of ownership) with sample firms.

[9]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.

TABLE 1

Summary Statistics of Stock Holdings and Transactions

Table 1 presents summary statistics of property–liability (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).

	Avg. No. of PL Insurers	All Stocks	PL Insurance Stocks		Other Stocks	
	(1)	(2)	(3)	(4) = (3)/(2)	(5)	(6) = (5)/(2)
Panel A. Stock Holdings						
No. of stocks	953	3,429.60	50.73	1.48%	3,378.87	98.52%
No. of shares (billion)	953	3.04	0.02	0.65%	3.02	99.35%
Value ($billion)	953	133.85	1.36	1.02%	132.49	98.98%
Panel B. Stock Buys						
No. of transactions (thousand)	866	65.36	0.97	1.50%	64.39	98.50%
No. of stocks	866	3,344.07	49.40	1.47%	3,296.47	98.58%
No. of shares (billion)	866	0.91	0.01	1.06%	0.90	98.94%
Value ($billion)	866	33.11	0.43	1.39%	32.68	98.61%
Panel C. Stock Sells						
No. of transactions (thousand)	853	60.47	0.93	1.53%	59.54	98.47%
No. of stocks	853	3,329.47	50.20	1.50%	3,281.07	98.55%
No. of shares (billion)	853	0.87	0.01	1.31%	0.86	98.69%
Value ($billion)	853	27.43	0.43	1.53%	27.00	98.47%

Specifically, stock holdings are merged with their most recent[10] stock information at the end of 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.

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 Appendix Table A1. Our stock holdings sample includes 968,852 insurer-stock-year observations, our stock buys sample includes 980,425 insurer-stock-day observations, and our stock sells sample includes 906,990 insurer-stock-day observations. Table 1 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 $133.85 billion, stock buys are $33.11 billion, and stock sells are $27.43 billion.[11]

IV. Industry Bias

Our primary variable of interest is the deviation of a PL insurer's equity portfolio allocation across industries from that of the market portfolio. In the literature, the most widely used measure of portfolio bias is the weight on the stocks that investors tilt their portfolios toward in excess of the market's weights in the same stocks (e.g., Seasholes and Zhu (2010), Døskeland and Hvide (2011)). Following Seasholes and Zhu (2010), we scale the excess weight by the percentage

[10]The purpose of merging stock holdings with the CRSP database is to get the Standard Industrial Classification (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.

[11]See the Supplementary Material for additional summary statistics on the PL insurance industry.

of the market portfolio in these stocks. Thus, our measure of industry bias (IB) is calculated as follows:

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

where w_p represents the percentage of a PL insurer's portfolio in a specific industry and w_m represents the percentage of the market portfolio in that industry.[12] To test our hypotheses, we calculate PL insurers' industry bias in their own industry as well as other industries.

Table 2 reports that the average percentage of PL insurers' portfolio in PL stocks is 2.08%, and the average percentage of the market portfolio in PL stocks is 2.73%. The mean of the industry bias is −20.81%, and it is statistically significant. The median is −100%, implying that more than half of the insurers in our sample do not invest in their own industry. Overall, we find that contrary to the findings in prior studies on individual investors, PL insurers exhibit a negative industry bias by tilting their portfolios away from stocks in their same industry. The negative industry bias in the PL insurance industry provides initial support for Hypothesis 1.

Table 2 also reports PL insurers' portfolio allocation toward other industries. We use the Fama–French 12 industry classification scheme to define the major industrial sectors in which insurers are able to invest. To capture the possible familiarity effects of industrial proximity, we disaggregate the "money (finance)" industry classification to which PL insurers belong into non-PL insurance and noninsurance financial to arrive at 14 industries (excluding PL). Across all industries, PL insurers' portfolio allocation deviates significantly from market weights. On average, PL insurers overweight stocks in non-PL insurance, noninsurance financial, chemicals, and utilities industries, and they underweight most other industries. However, without conditioning on how correlated each industry is with the PL industry, it is not possible to draw conclusions on the motivation for this divergence from market weights. In our subsequent analyses, we provide a detailed examination of the effect of hedging and familiarity on PL insurers' portfolio allocation.

V. Hedging

A. Hedging Against the PL Insurance Industry

Although the negative portfolio bias of PL insurers' equity portfolio in their own industry provides initial evidence for the hedging-based theory, in this section, we provide more direct evidence for PL insurers' motive for hedging. Specifically, we obtain the financial data of PL insurers from the NAIC InfoPro database and

[12]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 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 analysis using these alternative measures and find that our results are qualitatively the same.

TABLE 2

Industry Bias

Table 2 presents the industry bias in the property–liability (PL) insurance industry and other industries. 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 an industry and w_m represents the percentage of the market portfolio in an industry. The significance of the mean is based on a *t*-test and its *p*-value is reported. The significance of the median is based on a Wilcoxon rank-sum test and its *p*-value is reported. The table also reports the mean and median of w_p, w_m, and IB across all insurer-year observations as well as the stock return correlation between each industry with PL insurance over the entire sample period.

	w_p		w_m		IB $(w_p - w_m)/w_m$				Correlation with PL Insurance
Industry	Mean 1	Median 2	Mean 3	Median 4	Mean 5	*p*-Value for Mean 6	Median 7	*p*-Value for Median 8	9
PL insurance	2.08%	0.00%	2.73%	2.62%	−20.81%	0.00	−100.00%	0.00	1.00
Other Industries									
Non-PL insurance	3.82%	0.00%	2.53%	2.34%	51.88%	0.00	−100.00%	0.00	0.84
Noninsurance financial	25.37%	13.75%	19.00%	19.11%	34.13%	0.00	−27.33%	0.00	0.83
Nonfinancial									
Consumer nondurables	5.04%	3.27%	5.66%	5.66%	−10.24%	0.00	−41.46%	0.00	0.74
Consumer durables	2.38%	0.00%	2.33%	1.55%	−5.98%	0.05	−100.00%	0.00	0.75
Manufacturing	6.61%	5.32%	6.67%	6.62%	−0.57%	0.62	−18.60%	0.00	0.77
Energy	7.21%	5.82%	8.17%	8.76%	−10.05%	0.00	−24.40%	0.00	0.59
Chemicals	3.68%	2.15%	3.17%	3.21%	15.67%	0.00	−32.55%	0.00	0.72
Business equipment	11.85%	10.33%	15.22%	14.77%	−22.02%	0.00	−31.69%	0.00	0.64
Telecommunication	3.97%	1.86%	5.10%	5.01%	−21.62%	0.00	−63.90%	0.00	0.71
Utilities	5.24%	0.75%	3.64%	3.66%	45.16%	0.00	−79.07%	0.00	0.63
Shops	6.71%	5.35%	7.23%	7.19%	−7.19%	0.00	−25.41%	0.00	0.73
Healthcare	9.23%	8.49%	9.72%	9.42%	−4.00%	0.00	−12.07%	0.00	0.69
Other	6.80%	3.94%	8.83%	8.35%	−24.06%	0.00	−54.17%	0.00	0.75

investigate whether PL insurers' portfolio tilt away from stocks in their industry is positively related to the riskiness of their nonfinancial income (i.e., underwriting risk). An implicit assumption in this analysis is that there is a positive correlation between PL insurers' nonfinancial income and stock returns of PL insurance stocks. To verify this assumption, we use stock return as a proxy for nonfinancial income and conduct both pooled and time-series regressions of PL insurer stock excess returns on PL insurance industry excess returns using CRSP daily and monthly data separately. The results show that a vast majority of the PL stocks comove with the industry.[13]

We test Hypothesis 2, that risk exacerbates hedging, by modeling portfolio tilt as a function of underwriting risk and controls. Because w_p is bounded between 0 and 1 and IB is bounded between -1 and $(1-w_m)/w_m$), we employ the Tobit model with random effects.[14] Our initial analysis examines industry bias only in the PL insurance industry, with a regression model written as follows:

$$w_p \text{ or IB} = f(\text{UND\_RISK}, \text{Controls}), \tag{2}$$

where UND_RISK denotes underwriting risk. 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 the underwriting loss ratio over the previous 5 years. The underwriting loss ratio is defined as the ratio of losses incurred and loss adjustment expenses to premiums earned.

The literature that investigates the role of investor characteristics in determining portfolio choice 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), and Keloharju et al. (2012)). However, few studies investigate the effects of firm characteristics on institutional investors' portfolio choice. Therefore, we construct insurer equivalents of individual investors' characteristics as control variables in our multivariate regression analysis. Following Døskeland and Hvide (2011), our controls capture investor characteristics such as 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. We measure industry experience by firm age (AGE), which is calculated as the natural logarithm of the number of years since commencement, and our measure of gross wealth is firm size (SIZE), which is calculated as the natural logarithm of total net admitted assets. We measure income by the volume of net premiums written (NPW_SIZE), which is calculated as the natural logarithm of total net premiums written. Listing

[13]In the pooled regression with CRSP daily (monthly) data, the coefficient estimate on the PL insurance industry excess return is 0.8078 (0.6483), which is statistically significant at the 1% level. Among the time-series regressions with CRSP daily (monthly) data, 118 of 122 regressions (106 of 115 regressions) report a positive and significant coefficient estimate on the PL insurance industry excess return.

[14]Insurance company regulations prohibit short selling in their equity portfolios, censoring the lower bound values of these dependent variables. Econometrically, 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-effects model. We perform a likelihood-ratio test, and the results from the test suggest that the random effects should be included in the model. The same specification test is used to select the random effects models that are estimated later in Tables 5 and 6.

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 the 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 year fixed effects in the model.

Ho et al. (2013) suggest several explanatory variables related to insurers' investment risk taking. Following Ho et al., we 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 extent of long-tail insurance (LONG_TAIL) is the percentage of net premiums written on long-tail lines.[15] Following Berry-Stölzle, Liebenberg, Ruhland, and Sommer (2012), business line diversification (LINE_DIV) is measured as the complement of the Herfindahl index of net premiums written (NPW) across 24 lines of business,[16] calculated as follows:

(3) $$\text{LINE\_DIV}_{i,t} = 1 - \sum_{j=1}^{24} \left(\frac{\text{NPW}_{i,j,t}}{\text{NPW}_{i,t}} \right)^2,$$

where $\text{NPW}_{i,j,t}$ denotes the net premiums written by insurer i in line j ($j = 1, 2, \ldots, 24$) in year t, and $\text{NPW}_{i,t}$ denotes the total net premiums written by insurer i in a given year t. Larger values of $\text{LINE\_DIV}_{i,t}$ 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,[17] calculated as follows:

(4) $$\text{GEO\_DIV}_{i,t} = 1 - \sum_{k=1}^{58} \left(\frac{\text{DPW}_{i,k,t}}{\text{DPW}_{i,t}} \right)^2,$$

[15] 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 inland marine, financial guaranty, earthquake, fidelity, surety, burglary and theft, credit, fire and allied lines, mortgage guaranty, and automobile physical damage.

[16] 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.

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

where $DPW_{i,k,t}$ denotes the direct premiums written by insurer i in state j ($j = 1, 2, \ldots, 58$) in year t, and $DPW_{i,t}$ denotes the total direct premiums written in a given year t. Because the U.S. insurance industry is regulated by each state, we use state fixed effects to control for unobservable effects of state regulations. We also include line-of-business fixed effects to control for the potential relation between specific business lines and risk appetite. Appendix B provides definitions of the variables.

Following the literature, we exclude insurers with nonpositive total net admitted assets or net premiums written and insurers with an organizational form other than stock or mutual (e.g., Che and Liebenberg (2017)). We also exclude insurers with a nonpositive market value of common stock portfolio. This screen eliminates almost 60% of insurers because they 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 Appendix Table A1. To perform multivariate regressions, we winsorize the underwriting risk (UND_RISK) and the reinsurance ratio (REINSURANCE) in our sample at the 1st and 99th percentile levels to reduce the potential effects of outliers.[18]

Our final sample for the hedging analysis consists of 1,407 insurers with 11,517 insurer-year observations. The sample represents, on average, 65.81% (70.84%) of the entire U.S. PL insurance industry in terms of net admitted assets (net premiums written) across all years during our sample period. The summary statistics for our sample are presented in Table 3. In this sample, we find that similar to the results in Table 2, the average proportion of PL insurers' investment in the PL insurance industry is 1.95% and the corresponding average industry bias is −26.41%, confirming a portfolio tilt away from their own industry.

TABLE 3

Summary Statistics for Hedging Analysis

Table 3 presents summary statistics of the sample in the hedging analysis. The number of observations is 11,517. All variables are defined in Appendix B.

Variable	Mean	Median	Min.	Max.	Std. Dev.	1st Quartile	3rd Quartile
w_p	0.0195	0.0000	0.0000	1.0000	0.0722	0.0000	0.0141
IB	−0.2641	−1.0000	−1.0000	47.7157	2.6565	−1.0000	−0.4696
UND_RISK	0.2304	0.0780	0.0110	10.8891	1.0046	0.0481	0.1297
AGE	3.7374	3.7612	0.0000	5.3706	0.8918	3.1355	4.5218
SIZE	18.7657	18.7019	11.5375	25.8412	2.0888	17.2028	20.1875
NPW_SIZE	17.5061	17.6125	5.0814	24.3479	2.3414	16.0834	18.9883
PUBLIC	0.2113	0.0000	0.0000	1.0000	0.4083	0.0000	0.0000
PTF_MV	15.4829	15.5714	1.0986	24.7698	2.6531	13.8679	17.2740
PTF_DIV	3.1025	3.4012	0.0000	7.8172	1.6521	1.9459	4.1897
MUTUAL	0.3380	0.0000	0.0000	1.0000	0.4731	0.0000	1.0000
REINSURANCE	0.3103	0.2506	0.0000	0.9390	0.2501	0.1021	0.4861
LONG_TAIL	0.7156	0.7817	0.0000	1.0000	0.2825	0.6520	0.9176
LINE_DIV	0.4205	0.5160	0.0000	0.8831	0.3040	0.0433	0.6890
GEO_DIV	0.4385	0.4736	0.0000	0.9676	0.3854	0.0000	0.8473

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

As previously discussed, we employ two dependent variables to test the relation between underwriting risk and portfolio tilt. The first dependent variable is the proportion of PL insurers' investment portfolio in the PL insurance industry (w_p). Column 1 of Table 4 reports the regression results. We find that the coefficient estimate on underwriting risk (UND_RISK) is negative and significant, implying that high underwriting risk leads PL insurers to tilt away from stocks in their industry.[19] The second dependent variable we use is industry bias (IB). Column 2 presents the results. It shows that the coefficient estimate on underwriting risk (UND_RISK) is also negative and significant. Examining their allocation to the

TABLE 4

Hedging Against the PL Insurance Industry

Table 4 presents the results from the regression of the portfolio tilt toward the property–liability (PL) insurance industry on underwriting risk. The dependent variables are the proportion of common stock portfolio (w_p) and industry bias (IB), respectively, in the PL insurance industry. The other variables are defined in Appendix B. The regression model is Tobit with random effects. For the regression with w_p as the dependent variable, the left-censoring limit is 0 and the right-censoring limit is 1. For the regression with IB as the dependent variable, the left-censoring limit is −1 and the right-censoring limit is $(1 - w_m)/w_m$. The result (χ^2) of the likelihood ratio test of $\sigma_u = 0$ is reported. σ_u represents the panel-level variance component. The number of observations is 11,517. ** and *** denote significance at the 5% and 1% levels, respectively.

	Dependent Variable	
	w_p	IB
Variable	1	2
Intercept	−0.3184***	−12.8295***
	(0.0480)	(1.7428)
UND_RISK	−0.0063***	−0.2118***
	(0.0022)	(0.0814)
AGE	0.0083	0.2655
	(0.0052)	(0.1876)
SIZE	−0.0012	0.0185
	(0.0043)	(0.1576)
NPW_SIZE	0.0071**	0.1728
	(0.0033)	(0.1196)
PUBLIC	0.0051	0.1846
	(0.0081)	(0.2997)
PTF_MV	−0.0001	0.0046
	(0.0017)	(0.0646)
PTF_DIV	0.0322***	1.2294***
	(0.0020)	(0.0738)
MUTUAL	−0.0065	−0.2241
	(0.0093)	(0.3388)
REINSURANCE	−0.0125	−0.5996
	(0.0116)	(0.4272)
LONG_TAIL	0.0114	0.4796
	(0.0132)	(0.4848)
LINE_DIV	−0.0423***	−1.6431***
	(0.0160)	(0.5918)
GEO_DIV	0.0064	0.0825
	(0.0141)	(0.5182)
Year fixed effects	Yes	Yes
Line fixed effects	Yes	Yes
State fixed effects	Yes	Yes
Likelihood ratio test of $\sigma_u = 0$ (χ^2)	2,957.47***	2,833.71***

[19]Please see the Supplementary Material for a decomposition of underwriting risk into its systematic and idiosyncratic parts.

PL insurance industry, the mean marginal effects are a 0.17% decline in investment and a 5.70% decline in industry bias for a 1-standard-deviation increase in underwriting risk. These findings are consistent with Hypothesis 2. Specifically, the higher the underwriting risk, the more PL insurers tilt their portfolios away from their industry.

In terms of the control variables, we find that the coefficient estimate on portfolio diversification (PTF_DIV) is positive and significant in both model specifications. Consistent with Døskeland and Hvide (2011), our finding indicates that having more stocks in the portfolio can mitigate the negative industry bias. In addition, the regressions show that the business line diversification (LINE_DIV) is negatively related to the portfolio tilt toward the PL insurance industry. Given that the underwriting risk is controlled, the negative relation implies that greater business line diversification leads to higher correlation of individual firms' performance with industry performance, which prompts insurers to bias their investment portfolios away from their industry.

B. Hedging Across Industries

The preceding evidence for hedging is provided from the perspective of portfolio tilt regarding PL insurers' own industry. If PL insurers underweight the PL industry to hedge nonfinancial income risks, we anticipate hedging behavior in allocation to other industries as well. More specifically, we expect that PL insurers will allocate more (less) capital to industries whose returns have a lower (higher) correlation with those of the PL insurance industry. This implies industry portfolio weights should be negatively related to the stock return correlation between that industry and the PL insurance. We therefore measure the correlation of each industry's returns with the PL insurance industry (IND_CORRELATION) across our entire sample[20] and perform Tobit regressions of an insurer's portfolio weight (w_p) and industry bias (IB) in each industry (specified in Table 2) on that industry's correlation with PL insurance (IND_CORRELATION).[21] Table 5 reports the results. In columns 1 and 2, we find that the coefficient estimates on industry correlation (IND_CORRELATION) are negative and significant, suggesting that PL insurers tend to allocate more (less) capital to industries that have a lower (higher) correlation with their own industry. This result provides evidence in support of hedging across industries.

For PL insurers, their incentives to hedge depend largely on their underwriting risk. With higher underwriting risk, PL insurers should have greater incentives to

[20]As the allocation decision is conditioned on expected correlations and we are not attempting to validate the forecasting ability of PL portfolio managers, we measure correlation over the entire sample as in Massa and Simonov (2006). This analysis is robust to using rolling, backward-looking, correlation measurement.

[21]We do not include the controls variables as in Table 4 because they lose economic sense in this specification. Specifically, the sum of the weights of holdings in all industries is 1, and an insurer cannot overweight or underweight all industries. Thus, the coefficients on the insurer-level control variables cannot be interpreted. The year fixed effects cannot be included because of the same problem, as an insurer cannot overweight or underweight all industries in any given year.

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TABLE 5

Hedging Across Industries

Table 5 presents the results of hedging across industries. The dependent variables are the proportion of common stock portfolio (w_p) and industry bias (IB), respectively, in an industry. IND_CORRELATION is the correlation between the value-weighted return of the property–liability (PL) insurance industry with another industry over the entire sample period. HI_UND_RISK is a dummy variable that is equal to 1 if an insurer's underwriting risk (UND_RISK) is equal to or greater than the median in a year and 0 otherwise. The regression model is Tobit with random effects. For the regression with w_p as the dependent variable, the left-censoring limit is 0 and the right-censoring limit is 1. For the regression with IB as the dependent variable, the left-censoring limit is −1 and the right-censoring limit is $(1 - w_m)/w_m$. The result (χ^2) of the likelihood ratio test of σ_u = 0 is reported. σ_u represents the panel-level variance component. The number of observations is 161,238. * and *** denote significance at the 10% and 1% levels, respectively.

	Dependent Variable			
	w_p	IB	w_p	IB
Variable	1	2	3	4
Intercept	0.0830***	0.2250*	0.0830***	0.2253*
	(0.0117)	(0.1169)	(0.0117)	(0.1169)
IND_CORRELATION	−0.1241***	−1.5795***	−0.1217***	−1.5371***
	(0.0156)	(0.1566)	(0.0157)	(0.1567)
IND_CORRELATION × HI_UND_RISK			−0.0044***	−0.0788***
			(0.0012)	(0.0141)
Likelihood ratio test of $\sigma_u = 0$ (χ^2)	96,416.69***	77,121.48***	96,350.37***	77,044.59***

hedge across industries. To shed light on PL insurers' hedging incentives, we include an interaction term between the industry correlation and a binary variable that represents high underwriting risk in the sample (HI_UND_RISK). HI_UND_RISK equals 1 if an insurer's underwriting risk (UND_RISK) is equal to or greater than the median in a year and 0 otherwise. Columns 3 and 4 of Table 5 present the results. We find that the coefficient estimate on the interaction term (IND_CORRELATION × HI_UND_RISK) is negative and significant, indicating that insurers tend to hedge more when faced with high underwriting risk. This finding is consistent with our prediction and further supports the insurers' hedging incentives.[22]

C. Hedging Within the PL Insurance Portfolio

To further examine the hedging motive, we delve into PL insurers' portfolio allocation within their industry at the stock level. We anticipate that for hedging purposes, PL insurers tilt their PL insurance portfolio toward (away from) stocks that are less (more) correlated with them. For the subsample of publicly traded PL insurers, we measure their correlations with each PL insurance stock (CORRELATION) in year t by using daily stock returns from year $t-3$ to $t-1$.[23]

[22]Our results for the cross-industry hedging analysis are robust to: i) calculating correlations on a rolling basis over years $t-3$ to $t-1$ to address contemporaneity concerns, ii) year-by-year regressions to identify sensitivity to specific periods, iii) a dynamic Tobit regression model to address the potential dynamic relation between portfolio allocation and hedging, and iv) correlation measured via an index for value-weighted industry correlation to incorporate firm-level controls.

[23]We focus on the measure of correlation between two insurers over a rolling time window rather than the entire sample period because it can more reasonably reflect the variations in correlation due to the idiosyncratic risk of each insurer. Our results still hold if the correlation for the entire sample period is used.

However, this measure cannot be applied to the entire sample, as the majority of the insurers in our sample (as well as the overall PL insurance industry) are privately held. We therefore develop several measures of geographic and business line proximity that capture operational similarity for each insurer and the PL stock it holds. The first measure of proximity we construct is the proportion of a stockholder's states (business lines) that overlap with those of a PL insurance stock in the combined states (business lines) of these two insurers, referred to as GEO_OVERLAP (LINE_OVERLAP).[24] The second measure of proximity is the cosine similarity between a PL insurance stock and its stockholder's business weights across all states (business lines), referred to as GEO_SIM (LINE_SIM). Although the former is more intuitive, the latter takes into account the proportion of business in each state (business line) and closely mimics the portfolio similarity in the literature (Girardi, Hanley, Nikolova, Pelizzon, and Sherman (2021)). Following Girardi et al., we calculate the cosine similarity measures as

$$\text{(5)} \qquad \text{GEO\_SIM} = \frac{w_{i,s} \cdot w_{j,s}}{\|w_{i,s}\| \cdot \|w_{j,s}\|}$$

$$\text{(6)} \qquad \text{LINE\_SIM} = \frac{w_{i,l} \cdot w_{j,l}}{\|w_{i,l}\| \cdot \|w_{j,l}\|},$$

where $w_{i,s}$ and $w_{j,s}$ are insurer i and insurer j's vectors of weights across all states, respectively, and $w_{i,l}$ and $w_{j,l}$ are insurer i and insurer j's vectors of weights across all business lines, respectively.

Table 6 presents the results for PL insurers' portfolio allocation within the PL insurance industry. The dependent variable is the proportion of an insurer's PL insurance stock portfolio in an individual stock ($w_{p,s}$). Column 1 reports a positive coefficient estimate on the return correlation between publicly traded PL insurers and the PL stocks in which they invest.[25] This finding is contrary to what a hedging argument suggests and implies that PL insurers' stock selection inside their own industry is influenced by similarity. This finding is further supported by columns 3, 5, 7, and 9, where the coefficient estimates on the measures of geographic and business line proximity are consistently positive and significant in the full sample. Although familiarity is likely the driving force behind allocating more capital to PL insurance stocks with a higher correlation, we expect that its impact depends on the incentive to hedge. We test whether the role of familiarity in stock selection is moderated by hedging incentives by interacting the return correlation and operational similarity measures with the binary variable for high underwriting risk (HI_UND_RISK). Results for regression models that include these interaction terms are reported in columns 2, 4, 6, 8, and 10. We find that the coefficient estimate

[24]For instance, suppose insurer A operates in California, Arizona, and Oregon and insurer B operates in Arizona, Oregon, Tennessee, and Florida. GEO_OVERLAP is calculated as 2/5 = 0.4.

[25]Please see the Supplementary Material for a summary of the correlations between public PL insurer stock returns.

TABLE 6

PL Insurance Portfolio Allocation

Table 6 presents the results of property–liability (PL) insurance portfolio allocation. The dependent variable is the proportion of an insurer's PL insurance stock portfolio in an individual stock ($w_{p,s}$). CORRELATION is the stock return correlation between a PL insurance stock and its stockholder in years $t-3$ to $t-1$. HI_UND_RISK is a dummy variable that is equal to 1 if a stockholder's underwriting risk (UND_RISK) is equal to or greater than the median in a year and 0 otherwise. GEO_OVERLAP is the proportion of a stockholder's states that overlap with those of a PL insurance stock in the combined states of these two insurers. GEO_SIM is the cosine similarity between a PL insurance stock and its stockholder's business weights across all U.S. states and territories. LINE_OVERLAP is the proportion of a stockholder's states that overlap with those of a PL insurance stock in the combined business lines of these two insurers. LINE_SIM is the cosine similarity between a PL insurance stock and its stockholder's business weights across all business lines. The regression model is Tobit with random effects. The left-censoring limit is 0 and the right-censoring limit is 1. The result (χ^2) of the likelihood ratio test of $\sigma_u = 0$ is reported. σ_u represents the panel-level variance component. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: $w_{p,s}$									
Variable	1	2	3	4	5	6	7	8	9	10
Intercept	−2.5794***	−2.5847***	−2.0465***	−2.0412***	−2.0563***	−2.0554***	−2.1019***	−2.0966***	−2.0513***	−2.0470***
	(0.3607)	(0.3609)	(0.2168)	(0.2162)	(0.2170)	(0.2171)	(0.2165)	(0.2161)	(0.2158)	(0.2151)
CORRELATION	0.5209***	0.5073***								
	(0.0817)	(0.0826)								
CORRELATION × HI_UND_RISK		0.0446								
		(0.0445)								
GEO_OVERLAP			0.0964***	0.1115***						
			(0.0194)	(0.0204)						
GEO_OVERLAP × HI_UND_RISK				−0.0357**						
				(0.0151)						
GEO_SIM					0.1250***	0.1392***				
					(0.0242)	(0.0256)				
GEO_SIM × HI_UND_RISK						−0.0315*				
						(0.0188)				
LINE_OVERLAP							0.2002***	0.2162***		
							(0.0280)	(0.0286)		
LINE_OVERLAP × HI_UND_RISK								−0.0517***		
								(0.0188)		
LINE_SIM									0.0799***	0.1027***
									(0.0210)	(0.0220)
LINE_SIM × HI_UND_RISK										−0.0551***
										(0.0163)
Likelihood ratio test of $\sigma u = 0$ (χ^2)	3,870.10***	3,860.86***	22,022.27***	20,964.34***	20,600.37***	20,585.05***	21,061.77***	20,995.80***	21,030.84***	20,967.87***
Stock and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	31,932	31,932	189,983	189,983	185,825	185,825	189,983	189,983	189,983	189,983

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on this interaction term is generally negative and significant, indicating that the tendency to overweight “similar” stocks is reduced for insurers that have an incentive to hedge underwriting risk.[26]

VI. Familiarity

Up to this point, we have primarily found support for the hedging-based theories. However, we have also found evidence suggesting some familiarity-based portfolio allocation within the PL insurance industry. It is unclear whether this familiarity is simply a behavioral bias or whether it is driven by asymmetric information. We investigate the nature of the familiarity in a similar manner to Seasholes and Zhu (2010) and Døskeland and Hvide (2011), by using 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 stocks in their industry earn superior returns. A positive alpha provides evidence for Hypothesis 4, that familiarity is informed.

The transactions-based, calendar-time portfolios approach employs transactions data and mimics 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, 6, 9, and 12 months, respectively. We calculate the value-weighted returns on the buys portfolio and sells portfolio and regress the return difference between these two portfolios (buys minus sells) of all PL insurers ($R_z^{\text{BUYS}} - R_z^{\text{SELLS}}$) on Fama–French 3 factors (i.e., excess market return, SMB, and HML) or Carhart 4 factors (i.e., excess market return, SMB, HML, and MOM). We obtain Fama–French 3 factors and the Carhart momentum factor (MOM) from Kenneth R. French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html). The models for the regressions are as follows:

$$(7) \qquad R_z^{\text{BUYS}} - R_z^{\text{SELLS}} = \alpha + \beta_1 \left(R_m - R_f\right) + \beta_2 \text{SMB} + \beta_3 \text{HML},$$

$$(8) \qquad R_z^{\text{BUYS}} - R_z^{\text{SELLS}} = \alpha + \beta_1 \left(R_m - R_f\right) + \beta_2 \text{SMB} + \beta_3 \text{HML} + \beta_4 \text{MOM},$$

where α denotes the abnormal return (alpha), $R_m - R_f$ denotes excess market return, SMB denotes the small-minus-big portfolio return, HML denotes high-minus-low (book-to-market) portfolio return, and MOM denotes the momentum

[26]The most appropriate option for modeling the economic relations between our dependent and explanatory variables in Tables 4, 5, and 6, is a panel Tobit with random effects. Because this specification does not allow for clustering of standard errors (Wooldridge (2002)), we also estimate alternative versions of these tables that use a pooled Tobit model with clustered standard errors. In the Supplementary Material, we report that the results in Tables 5 and 6 are quantitatively similar but in Table 4 underwriting risk is no longer significant. We show that the loss in statistical significance is due to the pooled analysis and not standard error clustering. As a likelihood-ratio test suggests that a pooled specification is inferior to a panel model with random effects, we do not believe these pooled results weaken our overall conclusions.

TABLE 7

Regressions with Transaction-Based Calendar-Time Portfolios

Table 7 reports results from regressions with transactions-based, calendar-time portfolios with a holding period of 3, 6, 9, and 12 months, respectively, in Panels A, B, C, and D. The regressions are based on the Fama–French 3-factor model and the Carhart 4-factor model (available on Kenneth R. French's website). The dependent variable is the return difference between the property–liability (PL) insurance industry buys portfolio and the PL insurance industry sells portfolio ($R_z^{\text{BUYS}} - R_z^{\text{SELLS}}$ of all PL insurers in PL insurance, non-PL insurance, noninsurance financial, and nonfinancial industries, respectively). The other variables are defined in Appendix B. All returns are expressed in basis points. The *t*-statistics are based on Newey–West standard errors with 5 lags and robust to heteroscedasticity and serial correlation of residuals. * and ** denote significance at the 10% and 5% levels, respectively.

	Dependent Variable: $R_z^{\text{BUYS}} - R_z^{\text{SELLS}}$							
	PL Insurance		Non-PL Insurance		Noninsurance Financial		Nonfinancial	
	3-Factor	4-Factor	3-Factor	4-Factor	3-Factor	4-Factor	3-Factor	4-Factor
	1	2	3	4	5	6	7	8
Panel A. Holding Period of 3 months								
A	1.9310*	1.8995*	0.6742	0.6578	0.6066	0.7096	0.4640	0.5333
(*t*-stat.)	(1.7229)	(1.6971)	(0.5711)	(0.5569)	(0.7625)	(0.8522)	(1.0808)	(1.2500)
No. of obs.	3,830	3,830	3,832	3,832	3,832	3,832	3,832	3,832
Panel B. Holding Period of 6 months								
A	2.6004**	2.5917**	0.4801	0.4723	0.4770	0.5362	0.1731	0.2338
(*t*-stat.)	(2.5393)	(2.5281)	(0.5724)	(0.5635)	(0.7674)	(0.8183)	(0.4970)	(0.6792)
No. of obs.	3,890	3,890	3,892	3,892	3,892	3,892	3,892	3,892
Panel C. Holding Period of 9 months								
A	1.8596*	1.8208*	−0.1701	−0.1309	0.3251	0.3632	−0.1778	−0.1198
(*t*-stat.)	(1.9227)	(1.8798)	(−0.2113)	(−0.1628)	(0.5875)	(0.6223)	(−0.5586)	(−0.3810)
No. of obs.	3,950	3,950	3,952	3,952	3,952	3,952	3,952	3,952
Panel D. Holding Period of 12 months								
A	1.1307	1.0600	−0.4317	−0.3808	0.2452	0.2923	−0.1124	−0.0560
(*t*-stat.)	(1.2584)	(1.1790)	(−0.5727)	(−0.5058)	(0.4749)	(0.5321)	(−0.3636)	(−0.1824)
No. of obs.	4,010	4,010	4,012	4,012	4,012	4,012	4,012	4,012

(winners-minus-lowers) portfolio return. Because all variables in this regression are daily returns, which are small in magnitude, we express them in basis points to facilitate the subsequent interpretation of α. The significance of α is tested by a *t*-test that is based on Newey–West standard errors with 5 lags and robust to heteroscedasticity and serial correlation of residuals. Appendix B provides definitions of the variables.

Columns 1 and 2 of Table 7 report the results from our transactions-based, calendar-time portfolios of PL insurance stocks. We find that when the holding period is 3, 6, and 9 months, the daily abnormal return (α) for holding PL stocks is positive and significant in both the Fama–French 3-factor model and the Carhart 4-factor model. Specifically, α ranges from 1.8208 to 2.6004 basis points daily, which can be translated into an annual return of roughly 4.71% or 6.80%, respectively, based on an average of 253 trading days per year. However, the alpha is not significant when the holding period is 12 months. The insignificant alpha in a longer holding period is consistent with the phenomenon of "alpha decay" found by Di Mascio, Lines, and Naik (2017). Overall, we find that PL insurers have an information advantage in investing in stocks in the PL insurance industry. Because proximity is an inexpensive route through which investors have a comparative advantage in collecting information, this result explains why PL insurers have a strong preference for stocks with a greater correlation with them in the PL insurance industry. By comparison, Table 7 also reports the results from the transactions-based, calendar-time portfolios of stocks in other industries including non-PL insurance, noninsurance financial, and nonfinancial industries. We do not find a significant alpha in any of these industries, implying that PL insurers are unlikely to have an information advantage when investing in other industries as opposed to their own industry.

Taken together, we find that even though PL insurers have an information advantage with respect to trades in other PL insurers' stocks, their exposure to underwriting risk results in a net portfolio tilt away from their own industry. Our results suggest that observable industry bias is a product of both familiarity and hedging, and that for PL insurers the hedging motive dominates the familiarity effect.[27]

VII. Conclusion

In this article, we investigate industry bias in PL insurers' common stock portfolios. There are two competing theories in predicting divergence from the market portfolio. The familiarity-based theory suggests that investors should tilt their portfolios toward equities in their own industry, whereas the hedging-based theory argues that investors should hedge their nonfinancial income risk by tilting their portfolios away from their own industry, or related industries.

We provide evidence in support of both familiarity and hedging. When PL insurers purchase shares in other PL insurers, they prefer firms that are similar to their own firm. This preference for familiar stocks appears to be informed, as PL insurers earn abnormal returns when investing in their own industry. However, when we examine their industry holdings, we find PL insurers underweight the PL industry as well as industries with returns correlated with the PL industry. This underweighting is larger in magnitude for insurers with greater incentives to hedge as a result of having higher underwriting risk. Thus, despite informational advantages from familiarity, the industry bias in PL insurers' equity portfolios appears to be driven by hedging.

[27]Given the hedging behavior that we identify is consistent with rational portfolio allocation, it is logical to examine whether this rationality extends to other potential biases identified in portfolio managers. We therefore examine the disposition effect (Shefrin and Statman (1985)) whereby individual and institutional traders choose to harvest capital gains while forgoing realizing capital losses (see, e.g., Dhar and Zhu (2006), Frazzini (2006), and Cici (2012)). Directly examining both paper gains/losses as well as all trades, we find no evidence of the disposition effect in PL insurer equity portfolios. Discussion and results appear in the Supplementary Material.

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Appendix Table A1

Data Screen

Appendix Table A1 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.

Screen Criteria	No. of Obs.
Panel A. Stock Holdings (Insurer-Stock-Year Observations)	
Obtain property–liability (PL) insurers' stock holdings (unaffiliated) from the National Association of Insurance Commissioners (NAIC) InfoPro database (Schedule D-Part 2-Section 2) (2001–2015).	1,292,954
Remove stock holdings with nonpositive number of shares or fair value.	1,279,602
Aggregate holdings of the same stocks for each insurer on each portfolio date (year-end) for each PL insurer.	1,184,388
Remove stock holdings that cannot be merged with the Center for Research in Security Prices (CRSP) database (most recent information in each year).	968,852
Panel B. Stock Buys (Insurer-Stock-Day Observations)	
Obtain PL insurers' stock buys (unaffiliated) from the NAIC InfoPro database (Schedule D-Part 3 and Part 5) (2001–2015).	1,394,770
Remove stock buys with nonpositive number of shares or actual costs.	1,351,234
Aggregate buys of the same stocks for each insurer on each transaction date for each PL insurer.	1,229,697
Remove stocks buys that cannot be merged with the CRSP database on each transaction date.	980,425
Panel C. Stock Sells (Insurer-Stock-Day Observations)	
Obtain PL insurers' stock sells (unaffiliated) from the NAIC InfoPro database (Schedule D-Part 4 and Part 5) (2001–2015).	1,474,635
Remove stock sells with nonpositive number of shares or adjusted carrying value.	1,414,770
Aggregate sells of the same stocks for each insurer on each transaction date for each PL insurer.	1,148,275
Remove stock sells that cannot be merged with the CRSP database on each transaction date.	906,990
Panel D. Financial Data (Insurer-Year Observations)	
Obtain PL insurers' financial data from the NAIC InfoPro database (2001–2015).	41,073
Remove PL insurers with nonpositive net admitted assets.	41,068
Remove PL insurers with nonpositive net premiums written.	32,082
Remove PL insurers that do not hold any publicly traded common stock.	13,426
Remove PL insurers that are neither mutuals nor stocks.	12,225
Remove PL insurers without sufficient information to calculate the variables in the hedging analysis.	11,517

Appendix B. Variable Descriptions

Hedging Analysis Variables

w_p: Proportion of an insurer's common stock portfolio in an industry.

IB: Industry bias of an insurer's common stock portfolio in an industry.

UND_RISK: Underwriting risk, as measured by the rolling standard deviation of the loss ratio over the previous 5 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.

LINE_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 the Herfindahl index of direct premiums written across all U.S. states and territories.

Asymmetric Information Analysis Variables

$R_z^{\text{BUYS}} - R_z^{\text{SELLS}}$: Return difference between the buys portfolio and the sells portfolio (buys minus sells) of all PL insurers.

R_z^{Buys}: Value-weighted return of the buys portfolio of all property–liability (PL) insurers.

R_z^{Sells}: Value-weighted return of the sells portfolio of all PL insurers.

$R_m - R_f$: Excess market return (obtained from Kenneth R. French's website).

SMB: Small-minus-big portfolio return (obtained from Kenneth R. French's website).

HML: High-minus-low (book-to-market) portfolio return (obtained from Kenneth R. French's website).

MOM: Momentum (winners-minus-losers) portfolio return (obtained from Kenneth R. French's website).

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S0022109020000708.

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