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Asset Manager Commonality and Portfolio Similarity

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Abstract

Asset managers are increasingly influential in financial markets. We use new regulatory as well as manually collected data on asset managers of life insurers, the largest institutional investors of corporate bonds, and find that insurers with the same asset managers have more similar portfolios and trades. This similarity increases further if the asset manager actively oversees the majority of both insurers' assets. Moreover, the effect intensifies the longer insurers share the same asset manager. Nevertheless, the effect is primarily driven by purchases rather than sales and the resulting increase in correlation of portfolio returns is relatively small, alleviating associated financial stability concerns.

Keywords: insurance companies; asset managers; portfolio similarity; financial stability; investment behavior

JEL Classification: G11, G18, G2

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1 Introduction

Asset managers, such as Blackrock, play an ever-expanding role in financial markets. Institutional investors, such as insurance companies and pension funds, often allocate their portfolios according to strategies designed or advised by external asset managers. While regulatory proposals in the past have focused on individual institutional investors (e.g. the Financial Stability Oversight Council's designation of MetLife as a systemically important financial institution), there has been increasing concern that the asset management industry may be playing an important role in financial stability through its influence on institutional clients. Indeed, the value of U.S. life insurers' corporate bond holdings associated with external asset managers has almost doubled between 2010 and 2020 to over $1 trillion.[1] Accordingly, the National Association of Insurance Commissioners (NAIC) has focused on the role of asset managers and their influence on the financial stability of the insurance sector.[2]

Motivated by this increased prominence of asset managers, this paper aims to explore a fundamental question: Does sharing the same asset manager lead to more similar corporate bond portfolios among life insurance companies, the largest institutional bondholders? We find that life insurance companies that share an asset manager do in fact have more similar portfolios, trading behavior, and portfolio returns. More specifically, insurers with overlapping asset management are more likely to hold and trade bonds from the same issuers, even though they could achieve the same portfolio goals through other issuers' bonds.

[1] See Section 2 for more details on the role of external asset managers in insurance industry.

[2] The NAIC has been collecting information on asset managers since 2002. In 2016, the NAIC began to collect more detailed information regarding to what extent unaffiliated (external) asset managers explicitly handle insurer investments. According to our communications with the NAIC, the reasoning for this higher level of scrutiny is that "additional disclosures will be important for regulators' ability to determine where additional risk may exist and where additional diligence is required."

The relevance of this question lies in the structure of the insurance industry and its broader implications for financial stability. Insurers hold a significant proportion of corporate bonds in the market, and decisions made by asset managers on behalf of multiple insurance companies could lead to portfolio overlap. Therefore, a sudden shift in the market, even if it is triggered by a subset of bonds, could lead to simultaneous portfolio losses for many insurers. Furthermore, if having the same asset manager consistently leads to more similar portfolios and trades, concentrated influence of asset mangers could amplify herding behavior in financial markets. Herding, in turn, may undermine financial stability during downturns even when individual insurance companies have a relatively small impact on the market.

We answer this question through an empirical analysis using a rich dataset of insurance companies' corporate bond holdings, as well as previously untapped regulatory data on asset managers of insurance companies. Using this data, we first calculate the cosine similarity of portfolios between pairs of life insurers, which allows us to measure the degree of overlap in the corporate bonds held by different insurance companies. Cosine similarity, a popular measure in computer science that has recently made inroads to finance, provides a numerical representation of how closely aligned two portfolios are, with a value of one indicating identical portfolios and zero indicating no overlap (Girardi et al. 2021). We then create the key explanatory variable in this analysis: whether two insurers share the same asset manager, which we derive from asset management disclosures. These disclosures include asset managers' names and identification numbers (Central Registration Depository Codes), enabling us to track whether insurers have listed the same asset managers over time. These codes also allow us to manually identify broker and dealers and separate them from investment advisors, as the latter are more directly involved with asset management and have a fiduciary duty whereas broker/dealers simply execute the trades. Our results suggest that sharing the same manager increases an insurer pair's portfolio similarity by about 20% and its trade similarity by about 55%.

We control for several factors that could confound the results, such as the possibility that insurers belonging to the same group share investment strategies as well as asset managers, or that there are time trends that drive asset manager choice as well as portfolio decisions. By including fixed effects that capture these confounding factors, we isolate the specific effect of sharing an asset manager from these factors. As an additional robustness test, we obtain similar results when we replace the dummy variable capturing whether the insurers have the same asset manager with a continuous variable capturing the similarity of insurers' asset manager rosters.

Nevertheless, there may still be endogeneity concerns – for example, our results might be driven by similar investment motives of insurers who then end up hiring the same manager to implement their strategy, rather than the manager driving the investment strategy. We explicitly address such endogeneity concerns by manually collecting data about closures of asset managers. We show that the portfolio similarity of insurers declines following the closure of a shared asset manager, an event that is exogenous to the portfolio choice of the insurance companies.

Our paper includes various additional analyses aiming to shed light on the mechanism underlying our empirical findings, as well as on their consequences. First, we use the additional information collected by the NAIC since 2016 regarding the extent to which external asset managers directly control an insurer's assets. We find that the increase in portfolio and trade similarity materializes even if a shared manager serves primarily as an advisor rather than as an active manager. However, the similarity increases even further if the shared manager actively manages the majority of both insurers' assets. Second, we show that both the portfolios and trades of insurers become more similar the longer they share an asset manager. This result suggests that, when an insurer starts sharing an asset manager with another insurer, it takes time for the manager's influence to manifest, consistent with a relationship based on trust that becomes stronger over time. In particular, the effect of sharing an asset manager doubles after about ten years of sharing the same manager.

We greatly benefit from and contribute to various strands of literature studying the asset management industry and institutional investors. Unlike our research, previous literature has primarily studied the influence of asset managers in the context of evaluating the performance of managers affiliated with mutual, pension, or hedge funds (e.g. Chen and Pennacchi 2009, Pennacchi and Rastad 2011, Anand et al. 2021). These types of funds have also been the focus of the Federal Reserve when they study asset managers in the context of financial stability (Board of Governors, 2023). In contrast, there is scant research on the role of external asset managers, both in general and more specifically in the context of the insurance industry. Most studies explore the risk profiles of insurers' bond portfolios or their responses to regulatory changes rather than focusing on how asset managers influence their investment strategies (e.g. Ellul et al. 2011, Becker and Ivashina 2015, Ozdagli and Wang 2020). Other papers study the portfolio similarity of insurance companies or banks and how this can lead to correlated trades without focusing on the role of asset managers (Girardi et al. 2021, Braeuning and Fillat 2024). Our paper, therefore, fills a critical gap in the literature by explicitly studying how asset managers influence insurance companies' investment decisions, and how this influence can increase the portfolio similarity of insurers sharing an asset manager. Moreover, our results suggest that asset managers can play a significant role in creating similar portfolios across institutional investors not only through their active management of portfolios but also through their advisory services.

Finally, we contribute to the policy discussion by studying the potential systemic risks associated with concentrated asset management. If many insurers are influenced by the same asset managers, the resultant portfolio similarities could increase market fragility. For example, in times of financial stress, coordinated sell-offs could propagate losses across a large portion of the industry, raising concerns about contagion and systemic risk. Nevertheless, we find that our results are driven more by correlated purchases than correlated sales, suggesting that coordinated sales due to shared asset management is of more limited concern. However, one can still be worried that shared asset management can potentially increase correlation of investment income between insurers, which can amplify the effect of economic downturns. However, we find that sharing the same asset manager increases insurers' portfolio return correlations by only around 1.5%.[3] Overall, our results suggest that while sharing the same asset manager can lead insurance companies to invest in similar portfolios, the associated financial stability concerns seem more limited. This result seems to be in line with recent research that highlights the stabilizing role of life insurance companies (Chodorow-Reich et al. 2021, Barbosa and Ozdagli 2021, Coppola 2024).

2 Asset Managers in the Insurance Sector

Asset managers have become increasingly pervasive in the insurance industry over the past decade. According to the Insurance Asset Outsourcing Exchange's annual survey, \$3.4 trillion in global insurer assets were managed by 58 investment managers at year-end 2021. This number was \$1.4 trillion by 40 investment managers at year-end 2013 (Clearwater Analytics, 2014, 2022).

[3] This result is also important because it illustrates that a large increase in portfolio similarity does not automatically translate to a large increase in return correlation. In particular, note that we can interpret the cosine similarity of portfolio weight vectors as the correlation between returns generated by two portfolios if every asset has returns that are independent and identically distributed. This property does not hold in the data and our results indicate that portfolio returns are overwhelmingly driven by common factors affecting the cross-section of bonds, which dwarf the specific influence of asset managers.

While U.S. insurers report up to 750 unique investment managers (including broker/dealers), the most frequently cited managers have varied little over time (Johnson and Carelus, 2023).

According to our estimates, over $1 trillion dollars in U.S. life insurer corporate bond par values were related to external investment advisors at year-end 2020 (Figure 1). Moreover, Figure 2 shows the value of corporate bonds related to the five most popular managers at year-end 2020. These values represent 53% of total corporate bonds in value where insurers cite an external manager, and 38% of all corporate bonds held by life insurance companies.

Overall, these statistics represent an increased reliance on asset managers by life insurance companies. Indeed, the value of corporate bonds advised or managed by these entities more than doubled since mid-2000s. Yet, this reliance seems to be concentrated towards a small number of asset managers. This pattern may pose a potential financial stability problem to the extent that it leads to coordinated investment behavior across insurers working with the same asset manager.

3 Data and Summary Statistics

3.1 Data

Our analysis includes data on institutional bond holdings, bond characteristics, and asset management disclosures over time. We obtain corporate bond holdings from insurer statutory filings collected by the National Association of Insurance Commissioners (NAIC). Specifically, Part 1 of NAIC Schedule D describes insurers' end-of-year corporate bond holdings as filed annually. Through these filings we view and keep insurers' unique identifier (NAIC code), as well as the 9-digit CUSIP ID and par value of each bond they hold. We use the Mergent Fixed Income Securities Database (FISD) and the Trade Reporting and Compliance Engine (TRACE) to obtain bond type data and returns, which are cleaned according to Dick-Nielsen (2009) and Dick-Nielsen (2014). Combining these sources, we construct a yearly dataset of corporate bond holdings from 2006 to 2020 for all life insurance companies. We then aggregate par values to the 6-digit issuer CUSIP level.

We obtain asset management disclosures from NAIC General Interrogatories data, which provides ample information on various aspects of insurers' operations and finances. Part 1 of this dataset (or "Common Interrogatories") asks insurers a litany of demographic questions. We focus on a subset of questions within the "Investment" category, one of which asks insurers to "identify all investment advisors, broker/dealers or individuals acting on behalf of broker/dealers that have access to the investment accounts, handle securities and have authority to make investments on behalf of the reporting entity." These entities are identified by name and a unique Central Registration Depository Code (CRD) assigned to all active investment advisors and broker/dealers by the Financial Industry Regulatory Authority (FINRA). For precision, we manually clean the data and remove those CRD codes that are identified solely as broker/dealers, rather than investment advisors, on FINRA's online BrokerCheck platform because investment advisors are more directly involved with asset management and have fiduciary duty whereas broker/dealers simply execute the trades. We then merge this data with Part 1 of Schedule D, yielding a yearly dataset of bond holdings where we also view the set of investment advisor entities (asset managers) insurers interact with in a given year.

Insurance companies started reporting their asset managers in 2002. While insurance companies were not required to distinguish between affiliated (internal) and unaffiliated (external) managers prior to 2016, we expand the sample by including the pre-2016 reports on asset managers in our analysis for several reasons.

First, in the post-2015 data, our measures of overlapping management are very strongly correlated when we use all reported managers instead of only unaffiliated managers. In particular, the indicator of manager overlap calculated using all reported managers and the indicator using only unaffiliated managers have a correlation coefficient of 0.95.[4] An important factor contributing to this high correlation is that insurers who report hiring a registered unaffiliated asset manager do not report hiring a registered affiliated asset manager in the overwhelming majority (83%) of cases.

Second, our empirical analysis includes controls that capture whether the insurers in an insurance company pair belong to the same insurance group. This control accounts for the overlapping management that can be attributed to affiliated asset managers working with the insurers under the same insurance group, which practically covers all cases: while, technically, it is possible that an asset manager is an affiliated manager for more than one insurance group, these instances represent less than 1% of cases in the post-2015 data.[5]

We include insurers if they have listed an asset manager at any point in the period of our sample. In this way, if they have listed a related asset manager in at least one year (say, 2007) their portfolio characteristics will be considered in every other year as well – even when their asset management disclosures are left blank. On average, around 40% the insurers who file Schedule D do not list an asset manager from 2006 to 2020 and are removed.

In the following section, we discuss the construction of portfolio similarity measure. Other variables used in the paper are discussed throughout the paper as they are introduced. Appendix A provides detailed definitions for all variables and Table I provides the summary statistics.

[4]The correlation coefficient for the continuous manager similarity measure discussed in our robustness test in Section 4.3 is 0.93.

[5]We show that while belonging to the same insurance group increases portfolio similarity, controlling for this effect does not change the estimated effect of asset manager overlap in any material way, which is consistent with the reported high correlation of our overlapping management measures discussed above.

3.2 *Similarity Measurement*

To quantify the similarity of insurers' portfolios, we utilize the cosine similarity procedure found in Girardi et al. (2021) applied at the issuer-level. That is, in each year we first construct a vector of issuer portfolio weights for a given insurance company based on the par value share of each issuer in that insurer's year-end corporate bond holdings. If an insurer does not invest in an issuer, its respective portfolio weight component is set to zero. By construction, the sum of portfolio weights equal to one.

We calculate the *portfolio similarity* between insurer j and k in year t using the following formula:

$$PortfolioSimilarity_{jkt} = \frac{w_{jt} \cdot w_{kt}}{\|w_{jt}\| \cdot \|w_{kt}\|} \tag{1}$$

where w_{jt} and w_{kt} are insurer j and k's portfolio weight vectors in year t. That is, we normalize the dot product of pair $i = \{j,k\}$'s portfolio weights by the multiplicative product of their vector lengths. Portfolio similarity is non-negative and bounded in the interval [0, 1]. Empirically this measure captures the cosine of the angle between the two portfolio weight vectors for a given insurer-pair. When a pair's portfolio similarity equals zero, their portfolios do not overlap and are entirely different. When a pair's portfolio similarity equals one, their portfolio weight vectors overlap completely. Summary statistics for our portfolio similarity measure are found in Table I.

One economic interpretation of portfolio cosine similarity is that it captures the correlation between returns generated by two portfolios if every asset has returns that are independent and identically distributed.[6] Accordingly, we also study the impact of asset manager commonality on

[6] To see this, let the return of each asset a have a distribution with mean $\bar{r}$ and standard deviation σ. Then, the covariance of portfolio returns would be $E[\sum_a w_{ajt}(r_{ajt} - \bar{r})w_{akt}(r_{akt} - \bar{r})] = \sigma^2 w_{jt} \cdot w_{kt}$; the variance of insurer j's portfolio return would be $E[\sum_a w_{ajt}(r_{ajt} - \bar{r})w_{ajt}(r_{ajt} - \bar{r})] = \sigma^2 \|w_{jt}\|^2$ and there would be an analogous expression

the correlation of returns between insurers' portfolios. This exercise addresses a financial stability concern of sharing asset managers, which is the increased likelihood of correlated income losses across insurance companies.

4 Empirical Results

4.1 Portfolio Similarity and Asset Management: Baseline Results

We study whether interacting with one or more of the same asset managers affects the portfolio similarity of two life insurance companies. We estimate the following three linear regression models:

$$PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + FixedEffects + e_{i,t} \tag{2}$$

$$\begin{aligned} PortfolioSimilarity_{i,t} = \beta_0 &+ \beta_1 SameManager_{i,t} + \beta_2 SameGroup_{i,t} \\ &+ FixedEffects + e_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} PortfolioSimilarity_{i,t} = \beta_0 &+ \beta_1 SameManager_{i,t} + \beta_2 SameGroup_{i,t} \\ &+ \gamma_1 (SameManager_{i,t} \times SameGroup_{i,t}) + FixedEffects + e_{i,t} \end{aligned} \tag{4}$$

where $PortfolioSimilarity$ is the portfolio similarity measure of life insurance pair i in year t, as defined in Section 3.2, and $SameManager$ is a dummy variable that takes value one if both insurance companies in pair i report at least one identical asset manager CRD code in year t. Equation (2) is the univariate regression of $PortfolioSimilarity$ on $SameManager$, with year and

for insurer j. Plugging these into equation (1) would show that $PortfolioSimilarity$ is the correlation of returns under the assumption that returns of assets are independent and identically distributed. A corollary is that the portfolio similarity will deviate from actual return correlation to the extent that there are common factors moving returns.

pair fixed effects. Equation (3) controls for the possibility that insurers in a given pair may have overlapping portfolios because they share an investment strategy while operating under the same group's umbrella. Specifically, we introduce an additional dummy variable, *SameGroup*, which equals one if the insurers share the same insurance group code in year t. Lastly, we include the interaction between *SameManager* and *SameGroup* in equation (4) to see if *SameManager* impacts those insurer-pairs in the same group differently than those pairs in separate groups. Standard errors are multi-way clustered at insurer-pair and year levels.

Table II illustrates our results for these regressions. Model 1 with just time fixed effects shows that insurers who interact with the same asset manager have more similar portfolios, as indicated by a statistically significant increase of 0.096 in $PortfolioSimilarity$. Model 2 shows that the coefficient of *SameManager* drops to 0.034 but is still statistically significant when including pair fixed effects. This coefficient implies that insurer-pairs with overlapping asset management have about 20% higher portfolio similarity than the average pair (0.034 of 0.156 from Table I). Moreover, Model 2 indicates that much of the influence of having the same manager in Model 1 may be rooted in idiosyncratic insurer-pair characteristics. Nevertheless, commonality in asset management still clearly increases insurer portfolio similarity.

Model 3 controls for the effects of being in the same insurance group. Being owned by the same parent company increases insurer-pair portfolio similarity by .045. Intuitively, those companies that belong in the same group may have more similar investment strategies or may have access to the same in-house expertise and information about issuers, which influences the various issuers they purchase from. Nevertheless, there is no material change in the size and significance of *SameManager*, implying that its impact is not absorbed by any group-specific effects. This is reaffirmed with the inclusion of the interaction term in Model 4, which continues to show the positive individual effects of *SameManager* and *SameGroup*. *SameGroup* now increases portfolio similarity of .035 instead of .045, while *SameManager* increases similarity by an almost identical amount of .032. Through Model 4, we find that having the same asset manager is just as impactful as being in the same insurance group in terms of portfolio similarity. The significant coefficient of the interaction term shows that being in the same group increases the effect of having the same manager by .021. This latter finding suggests that insurance companies in the same insurance group may be benefiting from economies of scale in implementing a particular portfolio when a common asset manager is involved in decision making, which makes their portfolios more similar.

Next, we study how asset manager commonality affects an insurer's new investment decisions. We start by studying the cosine similarity of changes in portfolio weights, which we call *delta similarity*. That is:

$$DeltaSimilarity_{jkt} = \frac{\Delta w_{jt} \cdot \Delta w_{kt}}{\left\|\Delta w_{jt}\right\| \cdot \left\|\Delta w_{kt}\right\|} \tag{5}$$

Since portfolio weights add up to one, changes in portfolio weights add up to zero by construction, and therefore this similarity measure effectively captures the Pearson correlation coefficient of the changes in portfolio weights.[7] Summary statistics for delta similarity can be found in Table I.

Table III represents our regression results using delta similarity as the dependent variable. Model 1 shows having a common asset manager leads an insurer-pair to have a greater delta similarity of .049 on average. As we include pair fixed effects in Model 2, this influence decreases to .017 but is still statistically significant. Including *SameGroup* in Model 3, or the interaction of *SameManager* and *SameGroup* in Model 4, does not have a significant impact on the coefficient of *SameManager*. Given that the average delta similarity is 0.03 (see Table I), delta similarity for

[7]This is simply a byproduct of the elements of Δw_{jt} adding up (and therefore averaging) to zero so that the sample covariance satisfies $cov(\Delta w_{jt}, \Delta w_{kt}) = \Delta w_{jt} \cdot \Delta w_{kt}$.

insurer pairs sharing an asset manager is about 50% larger than the delta similarity of an average insurer pair (compared to 20% for portfolio similarities). It is clear sharing an asset manager increases the similarity of changes in insurers' portfolios.

Our baseline results show that having the same asset manager increases the similarity of insurers' bond portfolios as well as their adjustments in portfolio weights. A natural question is whether the similarity of portfolio flows is driven by an increase or decrease in portfolio weights. Similarly, we look at the role of active sales and purchases. This analysis is important to evaluate the financial stability implications of our results because correlated sales, rather than correlated purchases, are the primary financial stability concern.

4.2 *A closer examination of portfolio changes and similarity measure*

To better understand the drivers of delta similarity, we now decompose those vectors that describe yearly changes in issuer portfolio weights. Specifically, we split these vectors, first keeping only their positive components in the computation of similarity measures in the numerator and then keeping only their negative components. Let $\Delta w_{it}^{+} = max\{0, \Delta w_{it}\}$ and $\Delta w_{it}^{-} = min\{0, \Delta w_{it}\}$. We therefore define *positive delta similarity* and *negative delta similarity* as:

$$PosDeltaSimilarity_{jkt} = \frac{\Delta w_{jt}^{+} \cdot \Delta w_{kt}^{+}}{\left\|\Delta w_{jt}\right\| \cdot \left\|\Delta w_{kt}\right\|} \tag{6}$$

$$NegDeltaSimilarity_{jkt} = \frac{\Delta w_{jt}^{-} \cdot \Delta w_{kt}^{-}}{\left\|\Delta w_{jt}\right\| \cdot \left\|\Delta w_{kt}\right\|} \tag{7}$$

For example, suppose an insurer holds bonds of five issuers and has a delta portfolio weight vector of [-.2, 0, .2, 0, 0] within a given year; that is, this insurer has transitioned some of their portfolio weight from Issuer 1 to Issuer 3 compared to the year prior. To isolate the effect of the positive components on delta similarity we replace all negative components (in this case -.2) with zero when computing the cross-insurer dot products in the numerator. We call this *positive delta similarity*. Similarly, to isolate the effect of the negative components we replace all positive components (.2) with zero. We call this *negative delta similarity*. The lengths in the denominator do not change from our original baseline specification. That is, they are equal to the length of the whole delta portfolio weight vector as before (in our example, the length of [-.2, 0, .2, 0, 0]). Adjusting similarity measures in this fashion and then implementing our prior regression analysis allows us to see which component contributes more to the effect of sharing an asset manager on overall delta similarity.[8]

Table IV panel A describes the results for the case of negative delta similarity. In Model 1 with just year fixed effects, having a common asset manager leads to an increase in negative delta similarity of .023. Much of this effect, however, is washed out with the introduction of insurer-pair fixed effects, as in Model 2 the coefficient decreases to .007. Introducing *SameGroup* in Model 3 and *SameManager* $\times$ *SameGroup* in Model 4 does not materially change this coefficient. In comparison, Table IV panel B shows that the coefficient of *SameManager* is larger for the positive delta similarity which starts at 0.036 and levels out at 0.012 after including control variables. Overall, we find that the positive portfolio weight changes contribute more than the negative changes to the overall influence of *SameManager* on our delta similarity measure.

The previous analysis includes all relevant positive and negative components of changes in portfolio weight vectors when recomputing cosine similarity measurements. Nevertheless, port-

[8]The remaining portion of delta similarity, that is, $DeltaSimilarity - PosDeltaSimilarity - NegDeltaSimilarity$ captures the contribution of dissimilar trades to overall similarity, that is $(\Delta w_{jt}^{+} \cdot \Delta w_{kt}^{-} + \Delta w_{jt}^{-} \cdot \Delta w_{kt}^{+})/(\left\|\Delta w_{jt}\right\| \cdot \|\Delta w_{kt}\|)$.

folio weights can change between years for reasons other than an insurer buying or selling more bonds of a given issuer in its portfolio. For example, given the ample number of issuers an insurer can choose to invest in, the insurer may decide to diversify its holdings in a given year by investing in bonds of issuers previously not held in its portfolio. This would lead to a decline in the portfolio weights of already-held issuers, even when the insurer has not actively sold these bonds. Such changes in portfolio weights are unlikely to be as much of a financial stability concern as an active sale of bonds.

To further delineate the effects of active trading we reconfigure our previous analysis to only keep those positive (negative) components of insurers' delta weight vectors that also correspond to tangible increases (decreases) in par value of bonds from a particular issuer. Table V panel A shows our results for the active decreases in portfolio weights, and panel B shows our results for the active increases. We find that the coefficients of *SameManager* remain almost identical to those in Table IV, suggesting that the effects we identify stem from active trades.

All together, these results paint an intriguing picture about insurers' investment similarity. Having the same asset manager leads to portfolio movements, whether positive or negative, that are more similar. Further, we see that this increase in similarity is ascribed to both buy and sell-side trades though the impact of buy-side trades is larger. Overall, commonality in asset management leads insurers to make more homogeneous investment decisions but the influence of correlated sales, which is the main financial stability concern, is more muted than the influence of correlated purchases.

4.3 A Continuous Measure of Manager Commonality

So far, we have used the *SameManager* dummy as our explanatory variable that captures overlapping asset management. This variable indicates whether insurers in a given pair hire *at least one* common asset manager. In practice, we find that insurers often hire multiple managers, with some employing up to 23 different advisory entities. Using *SameManager*, then, may not capture some nuances in the degree of asset manager overlap. For example, if insurers in a pair hire three managers each, their asset management is arguably more similar if all three managers are the same compared to the case where only one of the managers is the same.

To account for these nuances, we construct a measure of manager overlap called *continuous manager similarity*. For each insurer-pair, we calculate continuous manager similarity by implementing the cosine similarity procedure for insurers' manager weight vectors, which characterize the set of managers an insurer hires in each year and weights them equally. For example, in a universe of four managers where an insurer hires three, their manager weight vector would be given by: [.33, .33, .33, 0], while if they hired all four the vector would be [.25, .25, .25, .25]. Based on these weight vectors, continuous manager similarity therefore shares the same characteristics as our portfolio similarity measure as described in Section 3. Through continuous manager similarity, then, we are able to view any change in the set of overlapping managers for insurer-pairs over time. A limitation of this characterization is that it treats all hired managers equally in terms of their influence on an insurer's investment decisions. This assumption stems from the limitations of the data, which does not provide information regarding each individual asset manager's influence on an insurer's investment decisions.[9] Summary statistics of continuous manager similarity for our

[9]Since 2016, the NAIC collects information on whether more than 10% or more than 50% of assets are managed by an asset manager without breaking down the total by each entity. We use this information in Section 5 when discussing

baseline sample can be found in Table I.

We replicate our analysis in Table II and Table III using continuous manager similarity (*ManagerSimilarity*) instead of *SameManager*. We again find a significant and positive relationship between overlapping asset management and our portfolio similarity measurements (see Tables VI and VII). In the case of portfolio similarity (Table VI), if a pair's set of asset managers completely overlap, their portfolio similarity is greater by .046 on average – a coefficient that is somewhat larger than the effect of having a shared manager in Table II. In the case of delta similarity this value is 0.24, which is larger than the effect of having a shared manager in Table III. Overall, we still see a significant impact of manager commonality using this continuous manager similarity measure.

4.4 Natural Experiment: Closure of Asset Managers as Exogenous Variation in Manager Commonality

One may be concerned that our results do not imply that employing the same asset manager leads to greater similarity in insurer portfolios. For example, insurers who follow similar portfolio strategies might be choosing to employ the same asset manager. We explicitly address such endogeneity concerns by showing that the portfolio similarity of insurers declines following a reduction in their manager similarity due to an asset manager's closure, which is an event exogenous to the portfolio strategy of the insurance companies.

After an asset manager ceases operation, every pair of insurers employing this manager will

active vs. advisory management services by focusing on those insurance companies with at most one manager.

experience a change in manager similarity due to its closure. Regardless of what these insurance companies choose to do following the asset manager's closure (e.g. hiring a new manager or continuing without any manager) the change in manager similarity that is attributed to the closure of the asset manager is exogenous. Therefore, we can use this exogenous change as an instrumental variable for the change in manager similarity around the closure events.[10]

We identify asset manager closures using FINRA's BrokerCheck platform, individually checking the records of each CRD code in our sample to identify those that have become inactive over our sample period. We then construct our sample for each manager closure event by identifying insurer-pairs where at least one of the insurers employs this manager.[11] In particular, we require that the insurer has employed this manager in the year, or year before, that manager became inactive. We make this choice because there is no specific guideline by the NAIC on whether an asset manager that has ceased operations partway through the year should be reported by the insurance company; therefore, the insurer could last report the manager in the year of closure or the year before. We then keep observations three years before the pair experiences the closure, and up to three years after, to capture any immediate effects of manager closure on a pairs' portfolio similarity measure and to minimize any imprecision due to changes in manager similarity unrelated to manager closure.[12]

We create our instrument, $ClosureInfluence$, based on the effect an asset manager's closure has on an insurer-pair's continuous manager similarity, analogous to the continuous treatment effect in

[10] Alternatively, we can directly use the the exogenous change in manager similarity associated with the asset manager closure as the explanatory variable, analogous to the continuous treatment effect in a natural experiment. We can derive the result associated with this alternative exercise from the instrumental variable regressions as we discuss when presenting our IV results below.

[11] This construction method creates a more homogeneous sample but our results are not dependent on this method.

[12] More specifically, we identify and parse pairs year by year, assigning each within-pair observation a relative "time from death" (i.e. -3 if the observation is three years before the death takes place, 2 if it is two years after the death takes place, etc.), and finally stack all observations together for our complete regression sample.

a natural experiment. We use continuous manager similarity instead of our *SameManager* dummy because the former allows us to identify more observations where manager overlap has changed due to a manager becoming inactive; the latter measure only changes value after asset manager closure if the insurer-pair shared one manager. $ClosureInfluence$ is calculated according to how the continuous manager similarity for a pair would change if they no longer shared an inactive manager in the year of its closure. For example, if an asset manager of a given pair becomes inactive in a given year, we calculate a separate (hypothetical) continuous manager similarity by removing the inactive manager from the manager weight vectors right before the closure (that is, the component associated with the closed manager is set to zero and weights are reallocated). We then take the difference of the actual manager similarity right before closure and this hypothetical manager similarity to calculate $ClosureInfluence$. $ClosureInfluence$ is zero if a manager listed in a pair becomes inactive but is not overlapping between insurers in its year of closure or if the pair does not experience an asset manager closure in a given year.

We then run the following regression specification:

$$\Delta PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 \Delta ManagerSimilarity_{i,t} + YearFE + e_{i,t} \tag{8}$$

where $\Delta ManagerSimilarity$ is the first difference of continuous manager similarity for pair i in year t, instrumented by the value of $ClosureInfluence$, and $\Delta PortfolioSimilarity$ is the first difference of portfolio similarity for pair i in year t. This regression is based on changes of the variables in our previous analysis because our instrument ($ClosureInfluence$) captures exogenous changes in manager similarity. We implement year fixed-effects, but not insurer-pair fixed-effects, for proper comparison with our results in Table VI because first-differencing the data eliminates the insurer-pair fixed effects.

For reference, we start with the regression of portfolio similarity on continuous manager similarity in levels as we did in Table VI, including year and insurer-pair fixed effects for the subsample of observations used in this section. The coefficient estimates in Columns 1 and 2 in Table VIII, panel A, are similar to the full-sample regression in Columns 2 and 3 of Table VI, suggesting that our results in this section are materially unaffected by sample selection.

Our IV procedure takes place in Columns 3 and 4 of Table VIII, where Column 4 includes the change in *SameGroup* between years t-1 and t ($\Delta SameGroup$). The first stage regressions for Columns 3 and 4, found in panel B, confirm the relevance of our instrument with a statistically significant coefficient value of 0.46 and a large F-statistic of 72, which is significantly higher than the Stock and Yogo (2005) critical values. The IV estimate for the coefficient of manager similarity equals .086. This number, combined with the first stage estimated of the impact of $ClosureInfluence$ on manager similarity (0.46) from panel B, tells us that the direct impact of $ClosureInfluence$ is around 0.039 ($0.46 \times .086$). These results suggest that, if anything, the estimates in our previous regressions are a lower bound. Overall, our analysis here confirms the causal relationship between asset manager similarity and portfolio similarity.

5 Understanding the Mechanism

This section seeks to identify the mechanism through which asset manager commonality increases the similarity of insurers' portfolios. First, we show that the effects of overlapping management partially depend on the degree an asset manager directly controls a particular insurer's portfolio decisions. This suggests that while asset managers who merely work as investment advisors have significant influence in terms of creating portfolio similarity, there is an additional effect for those managers that directly command large swaths of insurer assets. Second, we find that the longer two insurance companies share the same asset manager, the more similar their portfolio holdings and their trades become. This result suggests that, when an insurer starts sharing an asset manager with another insurer, it takes time for the managers' influence to manifest, consistent with a relationship based on trust that becomes stronger over time.

5.1 Active Management vs. Advisory Services

The NAIC General Interrogatories data asks insurers to identify any entity that provides investment advice or invests on behalf of the company. A natural question is whether both active management services and advisory services lead to increased portfolio similarity. We characterize the difference between "active" and "advisory" as whether a manager is responsible for the actual allocation, investment or distribution of an insurer's assets. Empirically we measure this from two questions within the Interrogatories data, where from 2016 onward insurers are asked:

a) "For those firms [identified as related investment advisors] do any... unaffiliated with the reporting entity... manage more than 10% of the reporting entity's assets?"

b) "For those [unaffiliated firms]... [identified as related investment advisors], does the total assets under management aggregate to more than 50% of the reporting entity's assets?"

In other words, insurers identify whether any of the asset managers in their employ manage at least

10% or 50% percent of their assets.

These questions allow us to answer whether active management by a common external asset manager influences an insurer-pair's portfolio similarity differently compared to advisory services. Accordingly, we create dummy variables *ActiveManager*10 and *ActiveManager*50 to indicate whether both insurers in a pair responded "yes" to question a) or b) above. Due to the nature of the question posed by the NAIC, we can only identify whether pairs share the active manager if they report one manager. We thus restrict our sample to those insurer-pairs where both insurers reported at most one asset manager in their year-end filings. Furthermore, we remove pairs where both insurers hire one manager before 2016 as we cannot view to what extent this manager controls insurer assets.

We augment equation (2) and run the following regression:

$$\begin{aligned} PortfolioSimilarity_{i,t} = \beta_0 &+ \beta_1 SameManager_{i,t} + \beta_2 ActiveManager10_{i,t} \\ &+ \beta_3 ActiveManager50_{i,t} \\ &+ \gamma_1 (SameManager_{i,t} \times ActiveManager10_{i,t}) \\ &+ \gamma_2 (SameManager_{i,t} \times ActiveManager50_{i,t}) + Controls + e_{i,t} \end{aligned} \tag{9}$$

Results can be found in the first three columns of Table IX. In column (1) we replicate our baseline regression from column (2) of Table II for comparability and find *SameManager* to have a similar coefficient in both tables. In columns (2) and (3), we introduce the other terms in equation 9. The coefficient of *SameManager* shrinks by about half but is still significant, suggesting that manager overlap creates portfolio similarity of a pair of insurers even if the shared manager primarily serves as an advisor rather than directly managing a large share of both insurers' portfolios.

Moreover, the coefficient of $SameManager \times ActiveManager10$ is small and insignificant while the coefficient of $SameManager \times ActiveManager50$ is significant. These results suggest that the effect of sharing the same manager depends on the extent to which a manager controls insurer assets. We repeat these regressions for delta similarity in columns (4), (5), and (6), where we find similar results.

Overall, our results suggest that if a manager controls the majority of an insurer-pair's assets, this pair will exhibit greater portfolio and trade similarity relative to those insurer-pairs who merely share an investment advisor. Nevertheless, asset manager's less tangible influences on insurers' balance sheets, such as investment advice, seem to matter for portfolio similarity as well.

5.2 Length of Exposure to Overlapping Management

Our baseline and natural experiment results show that there is a gap in portfolio and delta similarity between those pairs that have a common asset manager and those that do not. However, they are mute about the relative adjustment of these similarity measurements over time. In particular, after controlling for pair fixed effects, manager similarity only changes when at least one insurer hires a new manager. The influence of this change may take time to develop as the insurer and manager build greater trust and a deeper relationship.

We shed light on this issue by construction two new variables, $SameManagerTicker$ and $Ticker$. *SameManagerTicker* measures the number of contiguous years a given insurer-pair has had one or more of the same asset managers. For example, if a pair has exhibited manager commonality in the past three years (as of year t) $SameManagerTicker$ takes the value of 3. $Ticker$, on the other hand, simply measures the number of years a given pair has been in the sample (as of year t). Qualitatively *SameManagerTicker* captures the cumulative effect of *SameManager* as portfolios adjust to their new equilibrium. *Ticker* is included as a control for any movement in similarity measures over time that may otherwise be unknowingly assigned to *SameManagerTicker*.

Our regression equation becomes:

$$
\begin{aligned}
PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + \beta_3 SameManagerTicker_{i,t} \\
+ Controls + e_{i,t}
\end{aligned}
\tag{10}
$$

where we are interested in the coefficient of *SameManagerTicker*. When doing this analysis, we drop those pairs that always have overlapping management for the length of our sample (that is, *SameManager* always equals 1 for the pair), because we do not know how long this pair has shared an asset manager, and therefore *SameManagerTicker* is not informative. Moreover, *SameManagerTicker* resets to zero when *SameManager* dummy goes back to zero.

Table X represents the results for these regressions using our portfolio similarity measure. *SameManagerTicker* enters as positive and significant in Model 1 and maintains these attributes when *Ticker* is included in Model 2, taking values of .0027 and .0025 respectively. We also interact both ticker variables with *SameGroup* as shown in Model 3, where the significance of *SameManagerTicker* remains. Overall, we find that there is gradual adjustment in portfolio similarity the longer a given pair has an overlapping asset manager. Specifically, if a pair has an overlapping manager for 10 years, their portfolio similarity doubles.

One can argue that these results may be partially attributed to the fact that life insurance companies cannot adjust their portfolios immediately due to adjustment costs (Ozdagli and Wang, 2020).

Nevertheless, they can adjust their trades immediately, which we will be able to observe in delta similarity. Table XI represents the results for the analogous regressions when using delta similarity as the dependent variable, where we again find significant coefficients for *SameManagerTicker*, which implies about a decade is needed for the delta similarity to double.

Overall, our results suggest that an asset manager's influence builds over time, which leads to greater portfolio similarity the longer an insurer pair shares a manager. Therefore, the strength of insurer-manager relationships matter as a mechanism to explain our main results.

6 Impact on Portfolio Returns

Having established asset managers as a force that increases the similarity of insurers' portfolios, we now study if this pattern contributes to increased correlation of investment returns. If insurers with common asset managers have more similar portfolios, one may also expect their investment returns to be more similar as well. Therefore, if portfolio coordination due to overlapping asset management is widespread enough, correlated investment income can generate financial stability concerns during economic downturns. For example, a significant downturn related to a relatively small number of issuers could lead to a rapid decay in life insurance balance sheets influenced by a manager who prefers to heavily invest in those assets.

We obtain monthly corporate bond return information from Wharton Research Data Services (WRDS). It is well known that insurers' assets tend to be long duration to match their liabilities (e.g., Ozdagli and Wang 2020). Therefore, their monthly returns are very highly correlated as changes in interest rates creates correlated changes in bond prices. To get a more precise estimate of returns influenced by common asset management, and not underlying duration, we net out the portion of monthly returns attributed to the duration of a particular bond. Duration information is calculated using information from TRACE. We then calculate the monthly return on a Treasury bond with the same duration using the zero-coupon yields calculated by Gurkaynak et al. (2007). Subtracting this risk-free return from the end-of-month return found in WRDS yields *excess returns* for that bond in that month.[13]

We calculate the correlation of two insurer companies' monthly returns in a given year and use these annual pairwise correlations in our baseline analysis as the dependent variable, instead of similarity measurements. For a given year, we keep only those insurers that have associated excess return information for every month, because if they are missing return information in any particular month their return correlations cannot be calculated in a comparable way across pairs. Summary statistics of excess return correlations can be found in Table I.

The results of our regression analysis can be found in Table XII. *SameManager* in Model 1 enters positive and highly significant with a value of .045, before dropping to .014 in Model 2 when including insurer-pair fixed effects. This shows that insurer-pairs with asset manager commonality have higher excess return correlations of .014 on average than those pairs that do not. This coefficient remains similar after introducing additional controls in Models 3 and 4. In the context of Table I, these results show that the magnitude of the impact of *SameManager* on excess return correlations is small, indicating only about a 1.5% increase in correlation for the average insurer pair (0.014 from Table XII vs. 0.83 from Table I).

In sum, while we do find that having common asset management leads to greater excess return correlations for a given insurer-pair, the effect is not large enough to conclude there may be negative financial implications related to coordinated management. This result is important because

[13]The regression results in this section remain similar when we use actual returns instead of excess returns.

it illustrates that a large increase in portfolio similarity does not automatically translate to a large increase in return correlation due to commonality of asset managers. In particular, note that we can interpret cosine similarity of portfolio weight vectors as the correlation between returns generated by two portfolios if every asset has returns that are independent and identically distributed (see Section 3.2). This property does not hold in the data and our results indicate that portfolio returns are overwhelmingly driven by common factors affecting the cross-section of bonds, which dwarf the specific influence of asset managers.

7 Conclusion

Our paper highlights the important role that asset managers play in shaping the investment behaviors and portfolio structures of institutional investors, specifically life insurance companies. We show that insurers sharing asset managers exhibit more similar portfolios and trading behaviors, which can contribute to systemic risk in times of financial market stress. This effects persists even when an asset manager serves primarily in an advisory role but becomes stronger if the manager directly manages a substantial portion of an insurer's assets. Moreover, the longer an insurer pair shares the same asset manager, the more pronounced this similarity becomes, which may exacerbate correlated market movements.

These findings have important implications for both regulators and institutional investors. While previous regulatory focus has been on the systemic importance of individual institutions, this paper suggests that commonality in asset management across institutions could also be a significant source of financial instability. In particular, the insurance sector's heavy reliance on a few large asset managers may lead correlated income losses or can create herding behavior, potentially amplifying market-wide risks during downturns. Nevertheless, our results suggest that the investment similarity we document is driven more by purchases rather than sales. Further, associated return correlations due to shared asset management is a very small component of overall return correlations. These results alleviate concerns related to financial stability.

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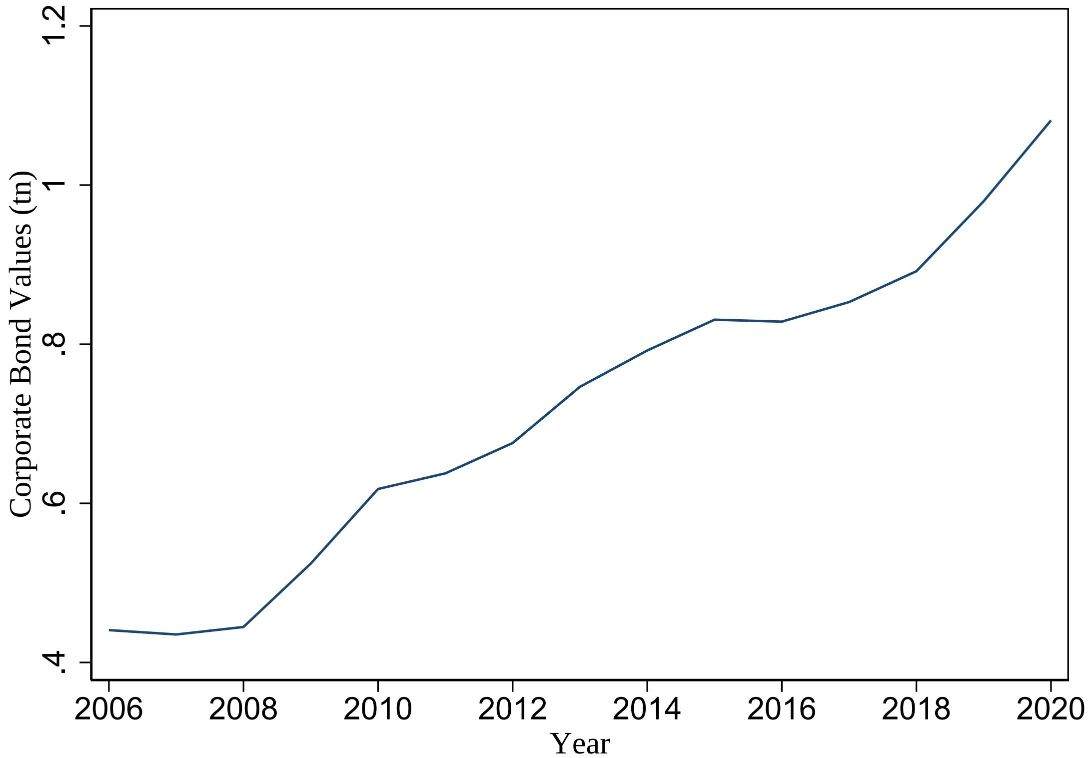
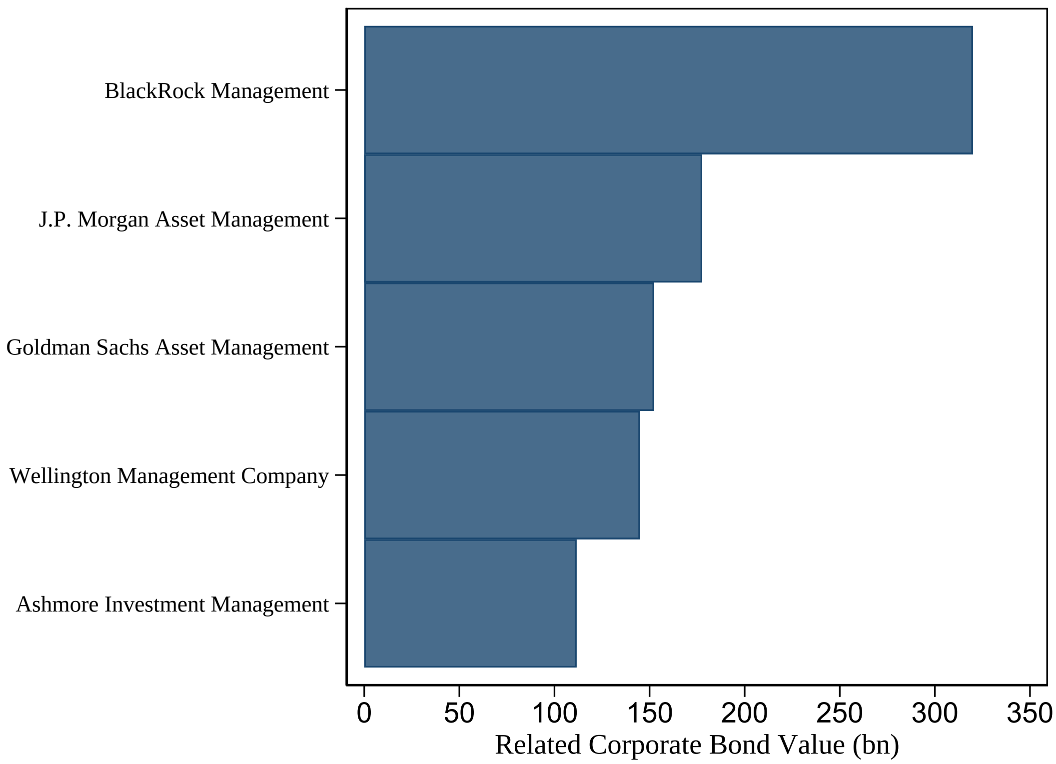
Figures and Tables

Figure 1: U.S. Life Insurer Corporate Bond Values Related to Asset Managers



Note: Related corporate bond values are defined as insurer year-end corporate bond holdings where, insurers report hiring an asset manager in NAIC General Interrogatories in that year. Starting 2016, we use insurers who report hiring an unaffiliated asset manager. “Asset Managers" include investment advisors and broker/dealers and are identified within NAIC General Interrogatories by Central Registration Depository (CRD) code.

Figure 2: Top 5 Most Popular Asset Managers by Corporate Bond Holdings of their Asset Management Clients, Year-End 2020



Note: Related corporate bonds are defined as the sum of insurer year-end corporate bond holdings where the insurers report hiring a given unaffiliated asset manager or investment advisor in NAIC General Interrogatories in 2020. Each manager reported in 2020 is assigned the sum of the value of corporate bond holdings from all insurers that report their Central Registration Depository (CRD) code in 2020. We characterize "BlackRock Management" as the sum of all related corporate bond holdings for BlackRock Financial Management Inc. and BlackRock Investment Management LLC, which are two unique subsidiary investment advisor entities owned by BlackRock Inc.

Table I: Summary Statistics for Similarity Measurements and Explanatory Variables

	Mean	Median	SD	Min	Max
PortfolioSimilarity	0.156	0.136	0.121	0	1
DeltaSimilarity	0.030	0.016	0.061	-0.976	0.995
NegDeltaSimilarity	0.028	0.018	0.032	0	0.963
PosDeltaSimilarity	0.035	0.021	0.042	0	0.935
ManagerSimilarity	0.617	0.577	0.277	.063	1
ReturnCorrelation	0.831	0.896	0.182	-0.845	1
SameManager	0.023	0	0.150	0	1
SameGroup	0.005	0	0.069	0	1
SameManagerTicker	3.634	3	2.973	1	15
Ticker	6.742	6	4.225	1	15
*ActiveManager*10	0.032	0	0.175	0	1
*ActiveManager*50	0.025	0	0.156	0	1

Note: Each observation in the data corresponds to an insurance company pair in a given year. *PortfolioSimilarity* is the cosine similarity of an insurer-pair i's corporate bond holdings in year t and is bounded on the interval [0, 1]. *DeltaSimilarity* is the cosine similarity of insurer-pair i's change in portfolio weights between year t-1 and t and is bounded on the interval [0, 1]. *ManagerSimilarity* is the cosine similarity of insurer-pair i's manager weight vectors in year t, which capture the external asset managers each insurer hires in year t. *ReturnCorrelation* is the correlation of an insurer-pair i's return vectors in year t. Return vectors are made up of components that capture the monthly average excess returns for an insurer. *SameManager* is a dummy variable that takes value one if both insurance companies in pair i report one of the same asset manager CRD codes in year t. *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. *SameManagerTicker* tracks the number of contiguous years an insurer-pair i has had overlapping management as of year t, and *Ticker* tracks the number of contiguous years an insurer-pair i has existed in the sample as of year t. *ActiveManager*10 and *ActiveManager*50 are dummy variables that indicate whether both insurers within a pair claim their hired manager actively manages either 10% or 50% of their assets in year t. Summary statistics for *ManagerSimilarity* and *SameManagerTicker* are tabulated based on the sample of insurer-pairs that have an overlapping asset manager. Summary statistics for *ActiveManager*10 and *ActiveManager*50 are tabulated based on the sample of insurer-pairs where each insurer hires at most one manager in any given year. See Appendix A for more details regarding the definitions and calculations of these variables.

Table II: The Relationship between Portfolio Similarity and Overlapping Asset Management

VARIABLES	(1)	(2)	(3)	(4)
		PortfolioSimilarity		
SameManager	0.0956***	0.0339***	0.0330***	0.0320***
	(0.00314)	(0.00360)	(0.00350)	(0.00344)
SameGroup			0.0447***	0.0348***
			(0.00668)	(0.00707)
$SameManager \times SameGroup$				0.0205***
				(0.00641)
Observations	1,684,073	1,670,459	1,670,459	1,670,459
R-squared	0.0487	0.725	0.725	0.725
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We perform the following regression specification: $PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + Controls + FixedEffects + e_{i,t}$ where *PortfolioSimilarity* is the cosine similarity of an insurer-pair i's corporate bond holdings in year t, *SameManager* is a dummy variable that takes value one if both insurance companies in pair i report one of the same asset manager CRD codes in year t, and *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. We implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table III: The Relationship between Delta Similarity and Overlapping Asset Management

	(1)	(2)	(3)	(4)
VARIABLES		*DeltaSimilarity*		
SameManager	0.0492***	0.0170***	0.0160***	0.0151***
	(0.00289)	(0.00213)	(0.00205)	(0.00196)
SameGroup			0.0588***	0.0488***
			(0.00671)	(0.00610)
SameManager × *SameGroup*				0.0204**
				(0.00717)
Observations	1,422,557	1,399,908	1,399,908	1,399,908
R-squared	0.044	0.313	0.314	0.314
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We perform the following regression specification: $DeltaSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + Controls + FixedEffects + e_{i,t}$ where *DeltaSimilarity* is the cosine similarity of insurer-pair i's change in portfolio weights between year t-1 and t, *SameManager* is a dummy variable that takes value one if both insurance companies in pair i report one of the same asset manager CRD codes in year t, and *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. We implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table IV: The Relationship between Delta Similarity Components and Overlapping Asset Management

Panel A: Negative Delta Similarity

	(1)	(2)	(3)	(4)
VARIABLES		*NegDeltaSimilarity*		
SameManager	0.0233***	0.00704***	0.00678***	0.00642***
	(0.00162)	(0.00100)	(0.000978)	(0.000957)
SameGroup			0.0147***	0.0106***
			(0.00254)	(0.00230)
$SameManager \times SameGroup$				0.00824***
				(0.00258)
Observations	1,422,557	1,399,908	1,399,908	1,399,908
R-squared	0.031	0.331	0.331	0.331
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Panel B: Positive Delta Similarity

	(1)	(2)	(3)	(4)
VARIABLES		*PosDeltaSimilarity*		
SameManager	0.0356***	0.0126***	0.0118***	0.0113***
	(0.00147)	(0.00162)	(0.00154)	(0.00148)
SameGroup			0.0443***	0.0383***
			(0.00521)	(0.00428)
$SameManager \times SameGroup$				0.0123**
				(0.00464)
Observations	1,422,557	1,399,908	1,399,908	1,399,908
R-squared	0.050	0.420	0.421	0.421
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We perform the following regression specification in panel A:
$NegDeltaSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + Controls + FixedEffects + e_{i,t}$ where *NegDeltaSimilarity* is the cosine similarity of the negative components of insurer-pair i's change in portfolio weights between year t-1 and t, *SameManager* is a dummy variable that takes value one if both insurance companies in pair i report one of the same asset manager CRD codes in year t, and *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. Similarly in panel B we perform the following:
$PosDeltaSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + Controls + FixedEffects + e_{i,t}$ where *PosDeltaSimilarity* is the cosine similarity of the positive components of insurer-pair i's change in portfolio weights between year t-1 and t. In either case we implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01,** p<0.05, * p<0.1

Table V: The Relationship between Active Trades and Overlapping Asset Management

Panel A: Active Sells

	(1)	(2)	(3)	(4)
VARIABLES		*NegDeltaSimilarity*		
SameManager	0.0205***	0.00728***	0.00704***	0.00686***
	(0.00141)	(0.00101)	(0.000986)	(0.000955)
SameGroup			0.0133***	0.0113***
			(0.00237)	(0.00216)
$SameManager \times SameGroup$				0.00420
				(0.00263)
Observations	1,422,557	1,399,908	1,399,908	1,399,908
R-squared	0.036	0.284	0.284	0.284
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Panel B: Active Buys

	(1)	(2)	(3)	(4)
VARIABLES		*PosDeltaSimilarity*		
SameManager	0.0348***	0.0119***	0.0111***	0.0106***
	(0.00153)	(0.00160)	(0.00152)	(0.00144)
SameGroup			0.0432***	0.0368***
			(0.00547)	(0.00462)
$SameManager \times SameGroup$				0.0130**
				(0.00454)
Observations	1,422,557	1,399,908	1,399,908	1,399,908
R-squared	0.048	0.416	0.416	0.416
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We perform the following regression specification in panel A:
$NegDeltaSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + Controls + FixedEffects + e_{i,t}$ where *NegDeltaSimilarity* is the cosine similarity of the negative components of insurer-pair i's change in portfolio weights between year t-1 and t that also correspond to decreases in par value, *SameManager* is a dummy variable that takes value one if both insurance companies in pair i report one of the same asset manager CRD codes in year t, and *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. Similarly in panel B we perform the following:
$PosDeltaSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + Controls + FixedEffects + e_{i,t}$ where *PosDeltaSimilarity* is the cosine similarity of the positive components of insurer-pair i's change in portfolio weights between year t-1 and t that also correspond to increases in par value. In either case we implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table VI: The Relationship Between Portfolio Similarity and Continuous Manager Similarity

	(1)	(2)	(3)	(4)
VARIABLES		*PortfolioSimilarity*		
ManagerSimilarity	0.112***	0.0455***	0.0436***	0.0419***
	(0.00495)	(0.00425)	(0.00410)	(0.00407)
SameGroup			0.0426***	0.0358***
			(0.00655)	(0.00685)
$ManagerSimilarity \times SameGroup$				0.0179**
				(0.00774)
Observations	1,684,073	1,670,459	1,670,459	1,670,459
R-squared	0.043	0.724	0.725	0.725
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We perform the following regression specification:
$PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 ManagerSimilarity_{i,t} + Controls + FixedEffects + e_{i,t}$ where *PortfolioSimilarity* is the cosine similarity of insurer-pair i's corporate bond holdings in year t, *ManagerSimilarity* is the cosine similarity of insurer-pair i's manager weight vectors in year t, which capture the external asset managers each insurer hires in year t, and *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. We implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table VII: The Relationship Between Delta Similarity and Continuous Manager Similarity

	(1)	(2)	(3)	(4)
VARIABLES		*DeltaSimilarity*		
ManagerSimilarity	0.0725***	0.0243***	0.0220***	0.0201***
	(0.00424)	(0.00250)	(0.00230)	(0.00228)
SameGroup			0.0575***	0.0489***
			(0.00652)	(0.00633)
ManagerSimilarity $\times$ *SameGroup*				0.0222**
				(0.00878)
Observations	1,422,557	1,399,908	1,399,908	1,399,908
R-squared	0.044	0.313	0.314	0.314
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We perform the following regression specification:
$DeltaSimilarity_{i,t} = \beta_0 + \beta_1 ManagerSimilarity_{i,t} + Controls + FixedEffects + e_{i,t}$ where *DeltaSimilarity* is the cosine similarity of insurer-pair i's change in portfolio weights between year t-1 and t, *ManagerSimilarity* is the cosine similarity of insurer-pair i's manager weight vectors in year t, which capture the external asset managers each insurer hires in year t, and *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. We implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table VIII: The Relationship between Portfolio Similarity and Overlapping Asset Management: Natural Experiments using Asset Manager Closures

Panel A: Comparison of Fixed Effects Regressions vs. Natural Experiment (IV) Results

	(1)	(2)	(3)	(4)
VARIABLES	$PortfolioSimilarity$		$\Delta PortfolioSimilarity$	
$ManagerSimilarity$	0.0327**	0.0298**		
	(0.0105)	(0.00999)		
$SameGroup$		0.0498**		
		(0.0192)		
$\Delta ManagerSimilarity$			0.0857***	0.0858***
			(0.0151)	(0.0151)
$\Delta SameGroup$				-0.00465
				(0.00465)

Panel B: First Stage Regressions for IV Analysis

			$\Delta ManagerSimilarity$	
$ClosureInfluence$			0.457***	0.457***
			(0.054)	(0.053)
$\Delta SameGroup$				0.213***
				(0.079)
Observations	83,087	83,087	82,622	82,622
Year FE	YES	YES	YES	YES
Pair FE	YES	YES		
F-Statistic			72.28	72.44

Note: Each observation in the data corresponds to an insurance company pair within a given year. Our sample represents the set of insurer-pairs affected by a manager closure. That is, at least one insurer within a given pair must hire a manager in the year or year before its closure to qualify. Further, the manager must have been hired in the three years prior to its closure. Observations fall within this three-year period, and up to three years afterward, for a given pair. We perform the following regression in column (2):
$PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 ManagerSimilarity_{i,t} + \beta_2 SameGroup_{i,t} + FixedEffects + e_{i,t}$ where $PortfolioSimilarity$ is the cosine similarity of insurer-pair i's corporate bond holdings in year t, $ManagerSimilarity$ is the cosine similarity of insurer-pair i's manager weight vectors in year t, which capture the external asset managers each insurer hires in year t, weighted by the number of managers they hire, and $SameGroup$ is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. We perform the following regression in column (4): $\Delta PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 \Delta ManagerSimilarity_{i,t} + \beta_2 \Delta SameGroup + YearFE + e_{i,t}$ where $\Delta ManagerSimilarity$ and $\Delta SameGroup$ are the first difference of $PortfolioSimilarity$, $ManagerSimilarity$, and $SameGroup$, respectively, with year fixed effects. $\Delta ManagerSimilarity$ is instrumented by $ClosureInfluence$, which is the forecasted next-period decline in $ManagerSimilarity$ (all else constant) due to manager closures in year t. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table IX: The Effects of Active Management vs. Advisory Services on Portfolio Similarity and Delta Similarity

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		$PortfolioSimilarity$			$DeltaSimilarity$	
$SameManager$	0.0322***	0.0177***	0.0158***	0.0127***	0.00805**	0.00600***
	(0.00355)	(0.00270)	(0.00208)	(0.00461)	(0.00434)	(0.00232)
$SameManager \times ActiveManager10$		0.00191	0.00210		-0.00405	-0.00395
		(0.00896)	(0.00471)		(0.00992)	(0.00433)
$SameManager \times ActiveManager50$		0.0181*	0.0187***		0.0142	0.0149***
		(0.00943)	(0.00446)		(0.00875)	(0.00409)
$ActiveManager10$		-0.000432	-0.000456		-0.00557	-0.00561***
		(0.00346)	(0.000709)		(0.00373)	(0.000652)
$ActiveManager50$		0.0105***	0.0105***		0.00505**	0.00505***
		(0.00287)	(0.000786)		(0.00225)	(0.000718)
$SameGroup$			0.0373***			0.0499***
			(0.00284)			(0.00280)
Observations	767,692	767,692	767,692	616,311	616,311	616,311
R-squared	0.755	0.755	0.756	0.359	0.360	0.360
Year FE	YES	YES	YES	YES	YES	YES
Pair FE	YES	YES	YES	YES	YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. This sample represents pairs who hire either zero or one asset managers within a given year. Before 2016 we remove insurer pairs where each insurer hires one manager as we are unable to infer whether this manager actively controls more than 10% or 50% of insurer assets. We perform the following regression in column (3): $PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + \beta_2 ActiveManager10_{i,t} + \beta_3 ActiveManager50_{i,t} + \gamma_1(SameManager_{i,t} \times ActiveManager10_{i,t}) + \gamma_2(SameManager_{i,t} \times ActiveManager50_{i,t}) + \beta_4 SameGroup_{i,t} + e_{i,t}$ where $PortfolioSimilarity$ is the cosine similarity of an insurer-pair i's corporate bond holdings in year t, $SameManager$ is a dummy variable that takes value one if both insurance companies in pair i report one of the same asset manager CRD codes in year t, $SameGroup$ is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t, and $ActiveManager10$ and $ActiveManager50$ are dummy variables that indicate whether both insurers within a pair claim their hired manager actively manages either 10% or 50% of their assets in year t. In column (4) we perform the following regression: $DeltaSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + \beta_2 ActiveManager10_{i,t} + \beta_3 ActiveManager50_{i,t} + \gamma_1(SameManager_{i,t} \times ActiveManager10_{i,t}) + \gamma_2(SameManager_{i,t} \times ActiveManager50_{i,t}) + \beta_4 SameGroup_{i,t} + e_{i,t}$ where $DeltaSimilarity$ is the cosine similarity of insurer-pair i's change in portfolio weights between year t-1 and t. In either case we implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table X: The Effects of Length of Managerial Overlap on Portfolio Similarity

	(1)	(2)	(3)
VARIABLES		$PortfolioSimilarity$	
$SameManager$	0.0260***	0.0260***	0.0264***
	(0.00411)	(0.00407)	(0.00405)
$SameManagerTicker$	0.00266***	0.00253***	0.00228**
	(0.000745)	(0.000756)	(0.000791)
$Ticker$		0.00665***	0.00665***
		(0.00205)	(0.00205)
$SameGroup$	0.0407***	0.0406***	0.0427***
	(0.00680)	(0.00685)	(0.0107)
$SameManagerTicker \times SameGroup$			0.00261
			(0.00163)
$Ticker \times SameGroup$			-0.000735
			(0.00112)
Observations	1,664,336	1,664,336	1,664,336
R-squared	0.722	0.723	0.723
Year FE	YES	YES	YES
Pair FE		YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We remove pairs that have overlapping management in every period they exist. We perform the following regression in column (3): $PortfolioSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + \beta_2 Ticker + \beta_3 SameManagerTicker_{i,t} + \gamma_1(SameManagerTicker \times SameGroup) + \gamma_2(Ticker \times SameGroup) + FixedEffects + e_{i,t}$ where $PortfolioSimilarity$ is the cosine similarity of an insurer-pair i's corporate bond holdings in year t, *SameManager* is a dummy variable that takes value one if both insurance companies in pair i report one of the same asset manager CRD codes in year t, *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t, *SameManagerTicker* tracks the number of contiguous years an insurer-pair i has had overlapping management as of year t, and $Ticker$ tracks the number of contiguous years an insurer-pair i has existed in the sample as of year t. We implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table XI: The Effects of Length of Managerial Overlap on Delta Similarity

	(1)	(2)	(3)
VARIABLES		*DeltaSimilarity*	
SameManager	0.0113***	0.0114***	0.0123***
	(0.00224)	(0.00225)	(0.00216)
SameManagerTicker	0.00183***	0.00180***	0.00118***
	(0.000365)	(0.000368)	(0.000372)
Ticker		0.00161*	0.00162*
		(0.000842)	(0.000843)
SameGroup	0.0532***	0.0532***	0.0501***
	(0.00712)	(0.00713)	(0.00900)
SameManagerTicker × *SameGroup*			0.00594***
			(0.00180)
Ticker × *SameGroup*			-0.000656
			(0.000862)
Observations	1,393,898	1,393,898	1,393,898
R-squared	0.293	0.293	0.293
Year FE	YES	YES	YES
Pair FE		YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We remove pairs that have overlapping management in every period they exist. We perform the following regression in column (3): $DeltaSimilarity_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + \beta_2 Ticker + \beta_3 SameManagerTicker_{i,t} + \gamma_1(SameManagerTicker \times SameGroup) + \gamma_2(Ticker \times SameGroup) + FixedEffects + e_{i,t}$ where *DeltaSimilarity* is the cosine similarity of an insurer-pair *i*'s difference in corporate bond holdings between year *t* and *t*-1, *SameManager* is a dummy variable that takes value one if both insurance companies in pair *i* report one of the same asset manager CRD codes in year *t*, *SameGroup* is an additional dummy variable which equals one if insurer-pair *i* shares the same insurance group code in year *t*, *SameManagerTicker* tracks the number of contiguous years an insurer-pair *i* has had overlapping management as of year *t*, and *Ticker* tracks the number of contiguous years an insurer-pair *i* has existed in the sample as of year *t*. We implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Table XII: The Relationship between Portfolio Excess Bond Return Correlations and Overlapping Asset Management

	(1)	(2)	(3)	(4)
VARIABLES		*ReturnCorrelation*		
SameManager	0.0448***	0.0138**	0.0135**	0.0128**
	(0.00655)	(0.00489)	(0.00494)	(0.00479)
SameGroup			0.0199*	0.0126
			(0.0102)	(0.0123)
SameManager $\times$ *SameGroup*				0.0146
				(0.00901)
Observations	1,448,602	1,435,123	1,435,123	1,435,123
R-squared	0.138	0.403	0.403	0.403
Year FE	YES	YES	YES	YES
Pair FE		YES	YES	YES

Note: Each observation in the data corresponds to an insurance company pair within a given year. We perform the following regression specification: $ReturnCorrelation_{i,t} = \beta_0 + \beta_1 SameManager_{i,t} + Controls + FixedEffects + e_{i,t}$ where *ReturnCorrelation* is the correlation of an insurer-pair i's return vectors in year t. Return vectors are made up of components that capture the monthly average excess returns for an insurer. Excess returns are calculated by subtracting the risk-free return on comparable-duration zero-coupon bond from a listed bonds end-of-month return (RET_EOM) found in WRDS. *SameManager* is a dummy variable that takes value one if both insurance companies in pair i report one of the same asset manager CRD codes in year t. *SameGroup* is an additional dummy variable which equals one if insurer-pair i shares the same insurance group code in year t. We implement year and insurer-pair fixed effects. Standard errors are multi-way clustered at insurer-pair and year levels. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Appendix A: Variable Definitions

$PortfolioSimilarity$

- The cosine similarity of two insurers end of year portfolio weight vectors in a given year. An insurer's portfolio weight vector is constructed by weighting the par values of issuer specific corporate bond holdings against the aggregate par value of an insurer's corporate bond portfolio. Components of the portfolio weight vector therefore represent the relative makeup of issuers for an insurers aggregate corporate bond investment. We obtain reported end of year par value holdings for insurers from NAIC statutory filings, specifically Part 1 of Schedule D from 2006-2020. We identify corporate bonds based on 9-digit CUSIP classifications taken from TRACE and FISD.

$DeltaSimilarity$

- The cosine similarity of two insurers end of year portfolio weight change vectors in a given year. An insurer's portfolio weight change vector is characterized by the difference between it's current and prior year portfolio weight vectors (i.e. $PortfolioWeights_t$ - $PortfolioWeights_{t-1}$), where corporate bonds that are present in either year, but not both, are removed.

$NegDeltaSimilarity$

- The cosine similarity of two insurers end of year portfolio weight change vectors in a given year, where positive changes are removed (in other words, set to zero) when computing dot products in the numerator of similarity computation. Portfolio weight change lengths in the denominator remain unchanged.

PosDeltaSimilarity

- The cosine similarity of two insurers end of year portfolio weight change vectors in a given year, where negative changes are removed (in other words, set to zero) when computing dot products in the numerator of similarity computation. Portfolio weight change lengths in the denominator remain unchanged.

ManagerSimilarity

- The cosine similarity of two insurers asset manager vectors in a given year. Asset manager vectors are constructed by weighting dummy indicators that represent if a given manager was reported by an insurer in a given year by the total number of managers an insurer reports in that year. Components of asset manager vectors therefore represent not only which managers were hired by an insurer, but also the normalized influence of managers in a given year (or more simply, how many other managers were hired). Asset manager disclosures were taken from insurer NAIC statutory filings, specifically from the "Investment" section of General Interrogatories where insurers are asked to declare affiliated and unaffiliated investment advisors, during the period 2006-2020.

$\Delta ManagerSimilarity$

- The first difference, or one year change, in *ManagerSimilarity*.

ReturnCorrelation

- The correlation of two insurer's excess return vectors in a given year. Excess return vectors are constructed by taking the average of an insurer's excess corporate bond returns for each month in that year. We define excess returns as the difference between a bond's reported nominal end-of-month return and its computed risk free return as derived from comparable duration zero-coupon yields calculated by Gurkaynak et al. (2007). Nominal end-of-month returns were obtained from WRDS during the period 2007-2021.

SameManager

- A dummy indicator tracking if two insurers hire the same asset manager in a given year. More specifically, *SameManager* takes the value of 1 if each insurer within an insurer-pair reports at least one of the same CRD codes within NAIC General Interrogatories.

SameGroup

- A dummy indicator tracking if two insurers are in the same insurance group within a given year. More specifically, *SameGroup* takes the value of 1 if two insurers each report the same NAIC group code within NAIC General Interrogatories.

Δ*SameGroup*

- The first difference, or one year change, in *SameGroup*.

SameManagerTicker

- An indicator of how long a given insurance company pair has contiguously reported sharing at least one asset manager over the period 2006-2020, that is, how long *SameManager* has contiguously equaled 1 during this period.

Ticker

- An indicator of how long a given insurance company pair has contiguously existed within our sample, that is, how many contiguous years both insurers within a pair have reported corporate bond holdings within NAIC Schedule D at time t, where t is between 2006-2020. Insurers are also only included in our sample if they have at some point between 2006-2020 reported hiring an external asset manager within NAIC General Interrogatories.

$ActiveManager10$

- A dummy indicator for insurer-pairs that only report one unique manager, representing if both managers within said pair cite the manager as controlling more than 10% of their assets. Explicit questions related to direct asset management of insurer's portfolios exist within NAIC General Interrogatories between 2016-2020.

$ActiveManager50$

- A dummy indicator for insurer-pairs that only report one unique manager, representing if both managers within said pair cite the manager as controlling more than 50% of their assets. Explicit questions related to direct asset management of insurer's portfolios exist within NAIC General Interrogatories between 2016-2020.

$ClosureInfluence$

- The theoretical decline in *ManagerSimilarity* attributed to the closure of a mutual asset manager reported by an insurance pair, absent of any other changes in asset manager hiring. Manager closures are identified using FINRA's BrokerCheck platform over the period of 2006-2020.