Insurance Companies, Asset Managers, and Economies of Scale

work in progress

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Abstract

External advisers are increasingly common in the insurance sector, with BlackRock Financial Management Inc. being the most prominent, advising over 47 life insurers in the past six years. This study explores the implications of insurers relying on the same external adviser, particularly in terms of portfolio similarity among insurers. Using cosine measures, I find that insurers with the same advisors have portfolios that are three times more similar compared to those of unrelated insurers. Similar trends are observed between insurers and corporate bond mutual funds managed by the same advisors. To address concerns about endogeneity, I further analyze the SMCCF (Secondary Market Corporate Credit Facility), also managed by BlackRock during the Covid-19 crisis. I show that the SMCCF portfolio is significantly more similar to the portfolios of insurers advised by BlackRock than to those of other insurers. The findings suggest that external advisors may leverage economies of scale by purchasing similar assets for their clients. Importantly, increasingly similar portfolios among insurers and between insurers and other investors raise important concerns about growing systemic risk in the insurance industry.

1 Introduction

Last year, the National Association of Insurance Commmissioners (NAIC) published a report showing that over 50% of U.S. insurers outsourced investments to external asset managers in 2022. [1] Even more surprisingly, the number of large insurers (i.e. managing more than $ 10 billion) that hired unrelated investment managers has more than doubled between 2021 and 2022. Today, the amount of

[1]Source: NAIC report Percent of U.S. Insurers Outsourcing to Unaffiliated Investment Managers Remains Consistent at Year-End 2022

insurers' investments managed externally is huge. Clearwater Analytics estimates that in 2021 alone, over $3.4 trillion in global insurer assets were managed externally. A steady increase from $2.9 trillion in 2020 and $2.6 trillion in 2019.[2]

The reason for their involvement seems very natural: great expertise in specialized and broad fixed income roles, as well as in alternative investments[3]. Academics have already argued that this expertise does not seem to translate into sustainable better portfolio performance. Kim, Leverty, and Schmit (2023) shows that external asset manager only provide out-performance in the short term and that such out-performance is short-lived.

But another relevant aspect that has not been studied concerns risk. In particular, one important question is whether there exist portfolio similarities between insurance companies and other investors that externalize the management of their portfolios to the same outside adviser. Given that over half of life insurers use external advisers, the question is probably of interest for many academics and practitioners studying the composition of the investor basis and its implication in the financial markets. Importantly, given that most external asset managers that advise insurance companies also offer mutual funds to other investors (retail or institutional), the implication of this question have broad impact on the financial markets.

The answer to this question is far from obvious. On one hand, one could expect insurers and mutual funds portfolios managed by the same adviser to negatively co-move together. This relates to the theory of 'internal capital markets'. Niehaus (2016) shows that insurers groups move capital internally between insurance companies, depending on the regulatory and operational needs. At the asset manager level, one could envision that fund flows could be an incentive for advisers to move resources internally. For example, when mutual funds face outflows, one could think that the adviser could use stable insurance companies flows to buy the mutual fund's assets hence providing liquidity without the need to trade within costly OTC market. This idea is very sensible since Goldstein, Jiang, and Ng (2017) show that corporate bond mutual funds tend to be very sensitive to past performance while Becker and Ivashina (2015) show that insurers flows tend to be very stable over time. On the other hand, one could expect insurers and mutual funds portfolios within the same adviser to co-move positively. The reason is that there exists strong evidence of 'economies of scale' in the corporate bond market. Already Edwards, Harris, and Piowar (2007) show that transaction costs significantly decrease with the size of the trade in the corporate bond market. A natural implication could be that advisers leverage on these economies of scale by buying the same assets for their multiple clients in order to reduce transaction costs.

One natural issue in studying portfolios similarities across investors is given by endogeneity and possible reverse causality: which investor's portfolio may affect the other? To address this issue, I use the

[2]Source: NAIC report and Clearwater Analytics Insurance Investment Outsourcing Report – 2022 Edition.
[3]Source: Clearwater Analytics Insurance Investment Outsourcing Report – 2022 Edition

Fed intervention in the corporate market via the Secondary Market Corporate Credit Facility starting from May of 2020. The Federal Reseve appointed BlackRock Financial Management Inc. as the manager of the facility. Coincidentally, BlackRock has been the most popular external adviser among insurers for the past five years, managing over 47 insurers life insurer portfolios in the past 6 years. Hence, the (SMCCF) offers a unique opportunity to study possible relationships between different investors portfolios in the corporate bond market through an experimental setting. O'Hara and Zhou (2021) already show that the SMCCF and insurance companies were both essential providers of liquidity during the Covid-19 crisis. The fact that BlackRock was advising both the SMCCF as well as several insurers at the time provides a unique opportunity to study possible economies of scale across different investors portfolios in the corporate bond market.

In order to understand these these questions, I conduct an in-depth analysis of life insurers corporate bond portfolios. Corporate bonds are the largest investment of insurance companies portfolios. I construct insurer level portfolio holdings from their regulatory fillings and I manually collect data on external asset managers. I then merge the names of external asset managers with the name of the investment managers contained in the CRSP mutual fund database. This allows me to compare insurers portfolios to those of corporate bond mutual funds managed by the same advisor. I find strong suggestive evidence of economies of scale between different clients of asset managers. Insurance companies that share the same external company have portfolios that are three times more similar (in terms of cosine similarity) compared to the portfolios managed by unrelated companies. I also find a similar results between insurer and mutual fund portfolios. That is, the similarity level between insurers and mutual funds portfolios sharing the same asset manager is almost twice as large compared to insurers and mutual funds that do not share advisers. However, the similarity gets fully absorbed by investor and asset's characteristics. Finally, I show that during 2020, the portfolio managed by BlackRock for the SMCCF was more similar to the portfolio of insurance companies also related to BlackRock. This last result strongly suggests the existence of economies of scale in the corporate bond market.

The rest of the paper is developed as follows: the next session provides a brief literature review of the studies most closely related to mine, section 3 presents the data, section 4 presents the similarity measure and the result of between insurers and mutual funds, section 5 focuses on the similarity betweent the SMCCF portfolio and the portfolio from other insurers managed by BlackRock. Section 6 concludes.

2 Literature Review

This paper makes several contributions to the current literature. First it relates to an important and rapidly growing group of articles studying insurance companies as investors in the financial markets. Perhaps the most famous view of insurers as investors is provided by Chodorow-Reich, Ghent, and Haddad

(2020) who refer to life insurance companies as "asset insulators" because of their stable, long-term liabilities that allow them to ride out transitory dislocations in market price. Knox and Sørensen (2023) builds on this idea and shows that insurers with more stable insurance funding take more investment risk and hence higher returns. Several additional studies looked at specific aspects of insurers portfolio choices. A lot of studies have connected insurance companies portfolio choice to regulation. For example, Becker and Ivashina (2015) find evidence of reaching for yield that is the propensity to buy riskier assets in order to achieve higher yields. The authors explain that insurers face high capital requirements when holding low-rated bonds so they prefer to hold highly-rated securities instead. But within a credit rating, insurers systematically opt for bonds with higher credit risk (measured with CDS) and higher yield. Also related to credit risk, Ellul, Jotikasthira, and Lundblad (2011) show that insurance companies sell corporate bonds when these are downgraded. The authors explain that this is driven by capital requirements, and hence show that insurers that are more constrained by regulation are more likely to sell downgraded bonds. Also related to credit risk exposure, Becker, Opp, and Saidi (2021) analyze the effects of a reform of capital regulation for U.S. insurance companies in 2009 which lowered capital requirements for MBS on portfolio choice. The reform affected MBS and not other fixed-income adssets, as a result the authors find that insurance companies are much more likely to retain downgraded MBS compared to other assets. Other papers such as Sen (2022) look at hedging behavior of insurance companies. The author notices that regulation of insurance companies allow for different treatments of minimum return guarantees on variable annuities with similar economic risks. This in turn affects portfolio choice as insurers only tend to hedge the risks recognized by the regulator. This paper contributes to this literature by providing evidence of additional aspects that can affect portfolio choice of life insurers: economies of scale. Two papers that are closely related to the current study are Girardi, Hanley, Nikolova, Pelizzon, and Sherman (2021) and Kim et al. (2023). Girardi et al. (2021) examine portfolio similarity across life insurers. Their goal is to understand whether insurers that have similar portfolios tend to similar portfolios sales when facing a shock to assets or liabilities. The authors find that portfolio similarity can indeed be used to predict common selling of institutions. I build on their papers in several ways. First, I follow their approach and define portfolio similarity using vectors of portfolio weights and cosine similarity. Second, I explain that higher portfolio similarity can be a result of a relationship with similar external advisers and can be expanded between insurers and other investors that play a similar role in the financial markets (i.e. the Fed). The other study, Kim et al. (2023) is the first paper that looks at the presence of external advisers in the insurance industry. The authors focus on portfolio performance and find that external advisers lead to short-lived risk-adjusted excess returns that disappear over time. They also find no evidence that insurers using external advisers have higher or lower returns compared to those who don't. I complement to their paper by looking at the composition of the portfolios of insurers using external asset managers (or not). My focus is not on performance but rather on risk. I focus my attention on the similarity level between different the portfolios of life insurance companies and other investors (mutual funds, Fed). While they find that external asset managers have no significant long term impact on performance, I find that they do have significant impact on portfolio choice and hence systemic risk.

This paper also relates to a literature on liquidity in the corporate bond market. O'Hara and Zhou (2021) study the Covid-19 liquidity crisis and find that during the two weeks prior to the Fed interventions, the transactions costs soared, trade-size pricing inversted and dealers (especially non-primary dealers), shifted from buying to selling causing dealers' inventories to plummet. The authors find that the two facilities set up by the Fed in order to improve liquidity in the corporate bond market (i.e. the Primary Dealer Credit Facility, and the Secondary Market Corporate Credit Facility) stabilized the trading conditions. However, most of the impact of the SMCCF was found following its announcement (that is, in early April). This paper complements the results of O'Hara and Zhou (2021) by showing additional consequences of the SMCCF. In particular, by looking at the manager of the facility, BlackRock, I can relate the role of the Fed with the role of other investors in the corporate bond markets. My findings build on previous work on the characteristics of the corporate bond market. Early work by Schultz (2001) and Edwards et al. (2007) show that transaction costs decrease significantly with trade size in the corporate bond market. Harris and Piwowar (2006) find similar evidence in the municipal bond market. The intuition behind my paper is simple: an asset manager that advises multiple investors such as insurance companies, mutual funds, and the Fed, can leverage on economies of scale by buying large quantities of the same asset for its different clients. A related, yet different evidence, is provided by O' Hara, Wang, and (Alex) Zhou (2018) who show that insurance companies that are more active ('sophisticated') in the corporate bond market obtain better prices. The authors show that 'sophisticated' traders and those that are more centrally located in the dealer network can get better prices. It could be interesting to study in later works if the sophidtication of external asset managers can lead to different execution quality to their clients, the insurance companies.

Finally, this paper relates to a very active literature on mutual funds, and in particular corporate bond mutual funds. I manually collect the external asset managers in insurance companies statutory fillings and match them with the fund managers names in the CRSP mutual fund database. This allows me to compare portfolios of insurance companies to those of mutual funds advised by the same firm. A striking difference between insurance companies and mutual funds is investors flows stability. As mentioned above, insurers are investors with stable liabilities, and hence stable cash flows. Mutual funds to the contrary, are known to have volatile fund flows. With specific reference to corporate bond mutual funds, Goldstein et al. (2017) show a significant flow-to-performance relationship. The authors show that outflow sensitivity to bad performance is higher than inflow sensitivity to good performance. In addition, they show that sensitivity is higher when market illiquidity is high. These results are consistent with the theoretical foundation and evidence found in early work by Ippolito (1992), Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Lynch and Musto (2003), Huang, Wei, and Yan (2007). Given the high volatility of mutual fund flows and the features of the corporate bond market mentioned above, it would be interesting to study the following hypotheses. First, during normal times, do managers exploit economies of scale in order to buy similar assets for the mutual funds and the insurance companies that they advise? Second, during times of outflows, can asset managers use insurance companies stable flows to respond to mutual fund pressure and provide them with an internal source of liquidity? It is difficult to provide evidence at the adviser level for the second hypothesis because I do not have access to internal transactions between parties within group. But the idea that resources may flow within insurance groups from stronger to weaker entities is a known fact. In an earlier work Niehaus (2016) provides evidence of such 'internal capital markets' and shows that capital flows internally from entities with positive performance (net income plus unrealized capital gains) to those with negative one.

3 Data

I use different sources of data for my study. I focus on life insurance companies because of data availability. I study corporate bonds as they are the largest asset class in insurers portfolios. [4] Coincidentally, insurers are also the largest investors in the U.S. corporate bond market. [5] I obtain corporate bond portfolios and transactions from insurer level annual regulatory fillings from *Capial IQ Insurance Statutory Financials*. The relevant information is contained in schedule D parts 1, 3, 4, and 5. These documents refer to issuer-credit obligations that qualify under the bond definition of *SSAP No. 26R - Bonds* and *SSAP No. 43R- Asset Backed Securities*. Part 1, refers to the holding at the year-end. Part 3 refers to assets acquired within the year and still held at the end of the year. Part 4, refers to disposals of assets acquired in previous years. Part 5 refers to assets that were acquired and disposed during the year. I identify corporate bonds using the CUSIP code provided for each holding/transaction. I follow Dickerson, Mueller, and Robotti (2023) and take the subset of corporate bonds most used in the Finance literature. I obtain this subset of corporate bonds by applying the following filters to the issues present in Mergent FISD. The first filter requires that bonds are denominated in USD and traded in the United States. The second filter exclude private placements and bonds issued under Rule 144A, structured notes, equity liked or convertible. The third filter excludes floating coupon rates. After applying these filters, I obtain a list of 135,207 unique corporate bond cusip from Mergent FISD.

For each corporate bond and each quarter, I also compute several characteristics using data from Mergent FISD and Finra TRACE. In particular, I take the credit rating related to each bond from Mergent FISD and I follow the methodology suggested by Dickerson et al. (2023) that is I assign the latest credit rating from Standard and Poor, when available. When this rating is not available, I replace it with the rating from Moody's. I also use the data from FINRA TRACE in order to construct an illiquidity measure. More specifically, I define the number of days traded in the last quarter as the number of days in the last in the previous quarter in which the trading volume for the corporate bond exceeded $10,000.

[4]This is also in line with Ellul et al. (2011), and Becker and Ivashina (2015).
[5]See Koijen and Yogo (2022) for more.

For insurers' external asset managers, I collect data from the General Interrogatories section 29.05 of the Regulatory Fillings. This section provides a list of all investment advisors, investment managers, broker/dealers, and individuals that have authority to make investment decisions on behalf of the reporting entity. The list of names is then followed by two dummy variables: the first one (item 29.0597) equals 'yes' is the total assets under management of any of the firms/ individuals in the list above are greater than 10% of the reporting entity's invested assets. The second one (item 29.0598) equals 'yes' is the total assets under management are greater than 50% of the reporting entity's invested assets. The data is available from December 2015, so I collect data from all life insurers fillings thereafter. For the purpose of this study, I take all advisors of insurance companies that have more than 10% of their assets controlled by external asset managers. I find 362 insurance companies above this threshold. I then manually match these advisor names with CRSP Mutual Funds data. For every fund in the database, CRSP provides information about the fund advisor name (ADV_NAME). For each advisor in the insurers fillings I look for one or multiple advisor names in CRSP. Of the 362 insurance companies above the threshold, I find 241 companies that have at least one asset manager matched in the CRSP mutual fund database. On the mutual fund side, I find 104 unique asset managers in the CRSP Mutual Fund database that advise these insurance companies. Given my focus on corporate bond portfolios, I focus on the funds that invest more than 40% of their portfolio in corporate bonds. There are 2,619 such mutual funds. I further divide them into active and passive funds using the index flag provided by CRSP. I find 2,397 active funds and 222 passive funds. Despite the fact that there are many more active than passive funds, the two groups have similar AUM. I also collect fund's portfolio holdings from CRSP Mutual Fund database and focus on the set of 135,207 securities detailed above. The reporting is monthly, but in some cases, I observe that holdings are only disclosed once per quarter. Figure 1 shows a summary of the matched AUM for the different investors. These are the AUM related to the corporate bonds included in the study. The dotted lines show the results for the mutual funds, while the solid lines show the results for the insurers.

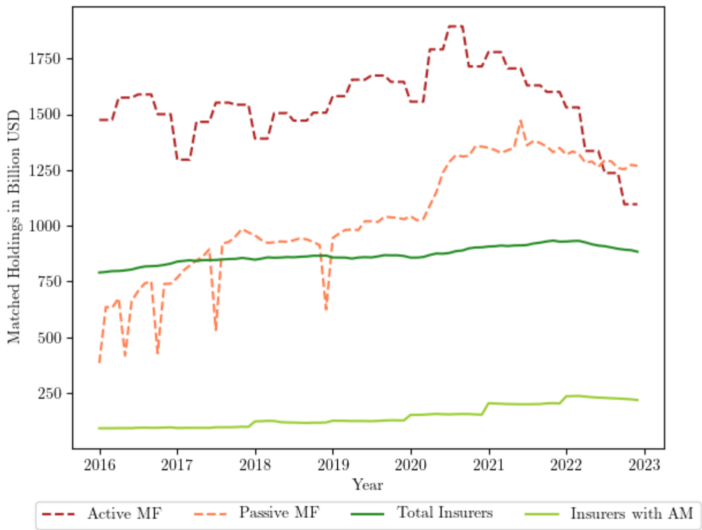
I also collect insurer's information from the statutory fillings. In particular, I construct measures of profitability (ROA), liquidity (cash and short term assets to capital and surplus), credit risk (high yield bonds to capital and surplus), capitalization, leverage and size using information from the quarterly statements available in S&P Capital IQ Pro.

Finally, I collect data on transactions and holdings of the Secondary Market Corporate Credit Facility from the Fed's reports to Congress Pursuant to Section 13(3) of the Federal Reserve Act in response to COVID-19. [6] For every security, I collect the data on the amount purchased of disposed as well as the date of the transaction. On May 11 2020, in the midst of the Covid-19 pandemic, the Federal Reserve Bank of New York entered an investment management agreement with BlackRock.[7] The SMCCF

[6] Data available at: Reports to Congress Pursuant to Section 13(3) of the Federal Reserve Act in response to COVID-19

[7] The contract identified BlacRock as the manager of the facility with the goal of advising and operationalizing the

Figure 1: Matched Corporate bond holdings



provided directions on the set of eligible and ineligible bonds as well as instruction for the construction of the Broad Market Index, a benchmark that was updated monthly. BlackRock role was to advise and run the operations of the facility whose objective was to support credit to employers by providing liquidity to the market for outstanding corporate bonds. The facility purchased corporate bonds between May of 2020 and December of 2020. At its peak, the SMCCF was buying over $100 million worth of corporate bond per day and reached a size of over $14 billion of AUM.At its peak, the facility was buying over $100 million worth of corporate bond per day.

4 Portfolio similarity and Economies of scale

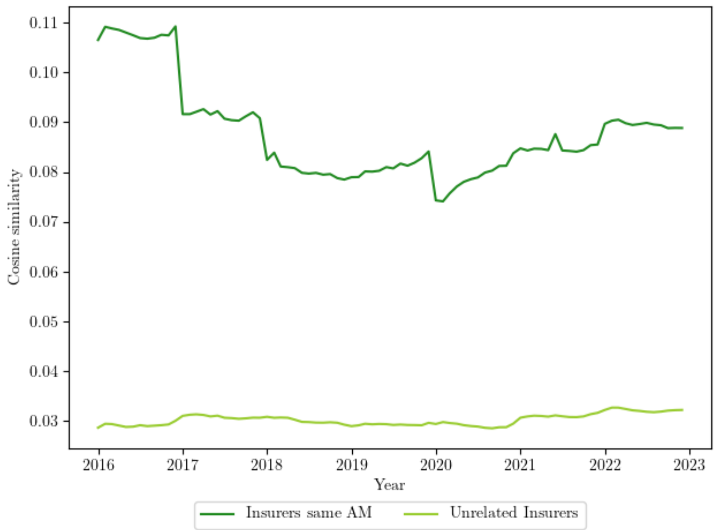
The core of this study revolves around the question of portfolio similarity. In order to measure the overlap between two investors portfolios, I use cosine similarity following Girardi et al. (2021) and define holding similarity (HS) as:

$$HS_{i,j,t} = \frac{\mathbf{w_{it}} \cdot \mathbf{w_{jt}}}{||\mathbf{w_{it}}|| \cdot ||\mathbf{w_{jt}}||} \tag{1}$$

where $\mathbf{w}$ is the vector of portfolio weights, i and j indicates different investors and time t indicates the month. The vectors of portfolio weights have size $[135, 207 \times 1]$, that is the size of the universe of corporate bond holdings that I consider. Similarly, I define net acquisitions similarity (AS) as:

SMCCF. The fees were a sum of a quarterly fixed management fee, and an AUM-based fee. The management fee consisted of $2 million for 2020 Q2, $1 million for 2020 Q3, $ 750,000 thereafter. The AUM-based fee varied depending on the quarter of the total program AUM and range between 0 and 2.5 basis points annualized. The contract also specified that BlackRock would not charge the facility for holdings of ETFs issued by BlackRock itself or by other entities.

Figure 2: Average holding similarity between insurers



$$AS_{i,j,t} = \frac{\mathbf{Net\ Acq_{it}} \cdot \mathbf{Net\ Acq_{jt}}}{||\mathbf{Net\ Acq_{it}}|| \cdot ||\mathbf{Net\ Acq_{jt}}||} \tag{2}$$

where **Net Acq** is the net acquisition of the month, that I define as the difference in the holding between beginning and end of the month that I measure in terms of par value. I then adjust for maturities and redemption. To do so, I set net acquisitions to zero on the month of maturity and if issued was entirely called back by the issuer (code E in Mergent FISD). In order to measure the similarity level across portfolios managed by the same adviser, I compute the average similarity between related insurance companies (i.e. that share the same adviser) and the average similarity between unrelated insurance companies. I compute both holding and transaction measures. That is, for every insurance company i advised by firm a, I define the average holding similarity for related and unrelated insurance companies as:

$$\begin{cases} Avg\ HS\ Related_{i,a,t} = \frac{\sum_j \mathbb{1}_{j\in a} HS_{i,j,t}}{\sum_j \mathbb{1}_{j\in a}} \\ \\ Avg\ HS\ Unrelated_{i,a,t} = \frac{\sum_j \mathbb{1}_{j\notin a} HS_{i,j,t}}{\sum_j \mathbb{1}_{j\notin a}} \end{cases} \tag{3}$$

Similarly I compute average transaction similarity for related and unrelated firms in the same way. I also compute these measures between insurers and mutual funds. A related mutual fund is a fund managed by the same adviser, while an unrelated fund has a different adviser. Figure 2 shows the average holding similarity between related and unrelated insurers over time. Figure 3 shows the average holding similarity between related and unrelated mutual funds.

Although the results show simple correlations, they provide very intuitive interpretations of the

Figure 3: Average holding similarity between insurers and mutual funds

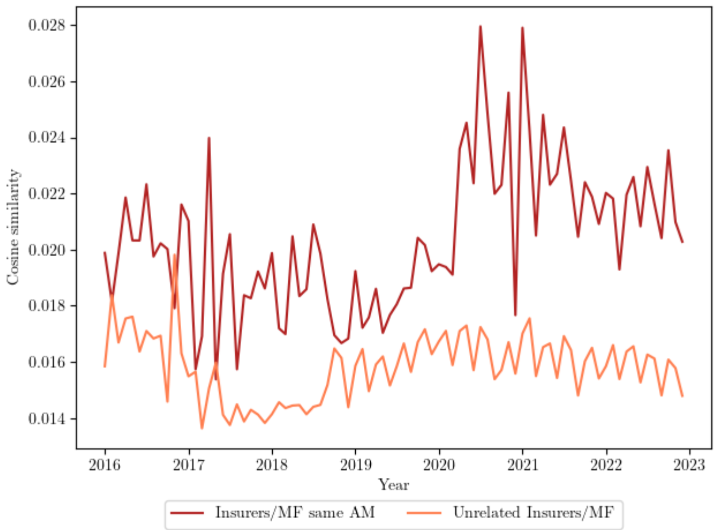


Table 1: Cross-sectional average holdings similarity

	Insurers portfolios		Insurers/MF portfolios	
	Same AM	Unrelated	Same AM	Unrelated
Average	0.077	0.023	0.018	0.012
St. Dev.	0.098	0.014	0.015	0.007
Min	0.000	0.000	0.000	0.000
25%	0.033	0.012	0.006	0.007
Median	0.054	0.022	0.014	0.011
75%	0.082	0.032	0.027	0.016
Max	0.744	0.074	0.110	0.040
Insurers	197	206	175	206

possible theories at play. For example, if external advisers were to move assets across portfolios according to the theory of internal capital markets from Niehaus (2016), then we would at least observe negative net acquisitions similarity between different investors in the same group. The assets that are disposed from one investor (negative sign) would be acquired by the other investor (positive sign), hence leading to overall negative net transactions for companies within the same group. To the contrary, if external advisers used economies of scale, we would at least observe positive net acquisition similarity between investors in the same group. The same asset would indeed appear in the same month for both investors, hence leading to overall positive net transactions similarity.

Tables 1 and 2 show the cross sectional average similarity between related and unrelated insurance companies.

Table 2: Cross-sectional average transaction similarity

	Insurers portfolios		Insurers/MF portfolios	
	Same AM	Unrelated	Same AM	Unrelated
Average	0.040	0.005	0.003	0.001
Std. Dev.	0.085	0.004	0.006	0.001
Min	-0.006	-0.001	-0.018	-0.003
25%	0.010	0.003	0.000	0.000
Median	0.020	0.005	0.002	0.001
75%	0.036	0.008	0.004	0.001
Max	0.797	0.018	0.042	0.007
Insurers	197	206	175	206

The results show that investors sharing the same adviser have higher portfolio similarity compared to investors that do not share the same adviser. Specifically, the cross-sectional average similarity between insurers in the same group is 0.077 while the average similarity for unrelated insurers is 0.023. So the holdings of insurers that share the same adviser is 3 times higher compared to the similarity of insurers that do not. Similarly, the average portfolio similarity between insurers and mutual funds in the same group is 0.018 which compares to 0.012 for unrelated insurers. So also across different investors portfolios, the similarity is higher for portfolios managed by the same advisers.

Similar results hold when looking at transactions. The average transaction similarity for insurers that share the same adviser is 0.04 while the average transaction similarity for unrelated insurers is 0.005. Between insurers and mutual funds related by the same adviser, the average transaction similarity is 0.003 while for unrelated insurers and mutual fund it is 0.001.

Overall these results provide strong suggestive evidence of economies of scale. Both the average holding and transaction similarity are significantly higher for investors with the same advisers. This could suggest that asset managers purchase the same corporate bonds for both their mutual funds and the insurance companies that they advise.

Given that there are multiple factors that could affect the asset allocation of insurance companies, I analyze the relationship between insurers holdings and mutual fund holdings at the security and quarterly level. In order to do this, I run a regression of insurers portfolio weights for a given security in a given month on the average portfolio weights of that same security in the mutual funds portfolios of related and unrelated entities. I also divide mutual fund portfolios into active and passive. Given that passive mutual funds have strict mandates that require them to replicate indexes very closely, one could expect that evidence of internal capital markets between different investors advised by the same firm could be concentrated between insurance companies (stable fund flows) and passive mutual funds (volatile fund flows and strict mandate). In this case, one would expect negative co-movement between insurance companies holdings and passive mutual fund holdings. In addition, I also control for other variables that may have an impact on the portfolio choice of life insurers. I use the variables from Ellul et al. (2011) and additional ratios used by AM Best to evaluate life insurers credit rating[8]:

- ROA,
- cash and short term assets to capital and surplus,
- high yield bonds (NAIC rating 5 and 6) to capital and surplus,
- leverage (assets in the general accounts divided by liabilities from general account),
- log size (USD value of asssets in the general account),
- capital and surplus divided by authorized control level capital.

I also control for corporate bond credit rating and liquidity. I build the credit rating variable from Mergent FISD data following Dickerson et al. (2023). In particular, I convert the rating for each bond in the sample on a numeric scale where 1 is AAA and 21 is C. I then take the latest rating from Standard and Poor and I replace it with Moody's rating if it is not available. For liquidity, I construct a liquidity measure that is equal to the number of days traded in the last quarter: the higher the measure the more liquid the bond. To construct the measure, I take all corporate bond transactions from TRACE and I consider that the bond was traded if the trading volume on a given day exceeds $\$10,000$.[9]

I also control for insurer and quarter level fixed effects given that I am interested in understanding whether insurers have more or less holdings for the bond that are also held by related mutual funds in that period.

I thus run the following regression of relative portfolio weights for insurance company i and corporate bond n in quarter t:

[8]See https://www3.ambest.com/ambv/ratingmethodology/OpenPDF.aspx?rc=250950 for a comprehensive overview of the methodology used by AM Best.

[9]This is in line with Dickerson et al. (2023).

$$
\begin{aligned}
w_{i,n,a,t} = \alpha &+ \beta_1 \cdot \frac{\sum_{j=i}^{J} \mathbb{1}_{j \in a \cap j \in active} w_{j,n,t}}{\sum_{j=i}^{J} \mathbb{1}_{j \in a \cap j \in active}} + \beta_2 \cdot \frac{\sum_{j=i}^{J} \mathbb{1}_{j \notin a \cap j \in active} w_{j,n,t}}{\sum_{j=i}^{J} \mathbb{1}_{j \notin a \cap j \in active}} \\
&+ \beta_3 \cdot \frac{\sum_{j=i}^{J} \mathbb{1}_{j \in a \cap j \in passive} w_{j,n,t}}{\sum_{j=i}^{J} \mathbb{1}_{j \in a \cap j \in passive}} \\
&+ \beta_4 \cdot \frac{\sum_{j=i}^{J} \mathbb{1}_{j \notin a \cap j \in passive} w_{j,n,t}}{\sum_{j=i}^{J} \mathbb{1}_{j \notin a \cap j \in passive}} + \gamma_{\mathbf{1}} \cdot \mathbf{controls_{i,t}} + \gamma_{\mathbf{2}} \cdot \mathbf{controls_{n,t}} + \delta_t + \delta_i + \epsilon_{i,n,t}
\end{aligned} \tag{4}
$$

Here a indicates the adviser and j indicates the mutual fund. Table [1] contains the results of this regression. The coefficients of this regression can thus be interpreted as the co-movement between insurance companies and mutual funds. The first two coefficients are the co-movements with unrelated active and passive mutual funds. This is common across all insurers in the sample. The second two coefficients can be interpreted as the additional co-movement between insurers and related mutual fund portfolios for insurance companies having an external adviser. The standard errors are double clustered at the security and quarterly level. Table 3 shows the result before and after adding cusip specific control variables.

Table 3: Regression of insurers portfolio weights on related and unrelated mutual funds portfolio weights

	Dependent variable: holdings	
	(1)	(2)
β_1	0.043***	0.059*
	(0.010)	(0.036)
β_2	0.149***	-0.867***
	(0.037)	(0.109)
β_3	0.088**	-0.104
	(0.040)	(0.089)
β_4	0.334***	0.821***
	(0.028)	(0.219)
Observations	19431699	1398942
Company FE	Yes	Yes
Quarter FE	Yes	Yes
Company controls	Yes	Yes
CUSIP controls	No	Yes
N. of groups	637	637
Note:	*p<0.1; **p<0.05; ***p<0.01	

Before controlling for cusip characteristics (Rating and Liquidity), the results confirm the analysis of cosine similarity from above. In particular, insurers portfolio weights significantly increase with portfolio weights of active and passive mutual funds advised by the same firm. However, the effect disappear after controlling for security level characteristics. This result is not surprising, after all. Corporate bond characteristics are an important determinant of insurers capital requirements, as already explained by numerous papers including Becker and Ivashina (2015), and Ellul et al. (2011). Overall these results do not suggest significant economies of scale or internal capital markets between insurers and mutual funds portfolios. After controlling for both insurer and security level characteristics, corporate bond portfolio weights seem to co-move positively with passive mutual funds and negatively with active ones.

5 SMCCF and BlackRock

The Covid-19 liqudity crisis provides an exogenous shock that allows us to better understand possible economies of scale between investors portfolios. In Q2 of 2020, the Fed signed an investment management agreement with BlackRock Financial Management Inc. in order to advise and operate the Secondary Market Corporate Credit Facility (SMCCF). The purpose of the SMCCF was to support credit by providing liquidity to the corporate bond market. O'Hara and Zhou (2021) already show that both insurers and the SMCCF acted as liquidity providers around this time. When BlacRock signed the agreement with the Fed in 2020, it was simultaneously advising over 47 life insurance companies. Hence, the question that arises naturally is whether the large inflows that BlackRock was receiving from the Fed had an impact on the portfolio choice of insurance companies also advised by BlackRock. In particuar, given that both insurers and the SMCCF were providing liquidity to the market by buying corporate bonds, BlackRock may have seeked lower transaction costs by purchasing the same bonds in large quantities and allocating them in the SMCCF and insurers portfolios. In other words, did BlackRock leverage on economies of scale in the bond market during the Covid-19 liquidity crisis?

I follow a similar approach to the one that I used in the previous section. First, I show the average holding and transaction similarity between the SMCCF portfolio and the portfolios of related and unrelated insurers (i.e. advised by BlackRock and not). Then, I use a regression in order to test whether portfolios of insurers advised by BlackRock increased their holdings in the corporate bonds that BlackRock also acquired for the SMCCF.

One challenge I encounter is that the SMCCF bought a large fraction of corporate bonds 'indirectly', that is via ETFs. More specifically, out of the $18 billion of the SMCFF AUM, $ 12 billion were ETFs, while $ 6 billion were corporate bonds. This was mainly driven by the fact that the SMCCF started buying ETFs first (starting from May 12 2020) and Corporate bonds after (starting from June 16 2020) in that the main concern faced by the Fed were corporate bonds and ETF mutual funds that experienced outflows for $200 billion alone during the last two weeks of March 2020.[10]In order to address

[10]See Boyarchenko, Cox, Crump, Danzig, Kovner, Shachar, and Steiner (2022) for more institutional details about the

Table 4: Comparison between portfolio weights of insurance companies advised by BlackRock and unrelated

	Not advised by BlackRock	Advised by BlackRock
Average	0.0041	0.0023
Std. Dev.	0.0155	0.0058
Min	0.0000	0.0000
25%	0.0005	0.0004
50%	0.0013	0.0010
75%	0.0037	0.0023
Max	1.0000	1.0000
Count	4080767	375809

this issue, I decompose the SMCCF's ETF holdings into their individual corporate bond components as follows:

$$SMCCF_{n,t} = \sum_{l=1}^{L} number\ of\ shares_{l,t} \times AUM_{l,t} \times w_{n,l,t} \tag{5}$$

where L are the ETFs held by the SMCCF, $number\ of\ shares_{l,t}$ is the number of shares held by the SMCCF in the ETF l in quarter t and $w_{n,l,t}$ is the portfolio weight of fund corporate bond n in ETF l in quarter t.

A challenge that I face is that insurers advised by BlackRock seem to have more diversified corporate bond portfolios (hence lower portfolio weights) compared to other insurers. Table 4 shows the average portfolio weight for insurers advised by BlackRock compared to others. The average weight for a corporate bond in a portfolio of an insurance company advised by BlackRock is 0.23%, which compares to 0.41% for other insurers. Hence, in order to account for diversification, I use relative portfolio weights, that is I simply divide the portfolio weights by the largest weight in the portfolio.

I then run the following regression that is similar in spirit to 4.

SMCCF.

$$
\begin{aligned}
\frac{w_{i,n,a,t}}{\max w_{i,t}} = \alpha &+ \beta_1 \cdot \frac{\sum_{j=i}^{J} \mathbb{1}_{j \in a \cap j \in active} w_{j,n,t}}{\sum_{j=i}^{J} \mathbb{1}_{j \in a \cap j \in active}} + \beta_2 \cdot \frac{\sum_{j=i}^{J} \mathbb{1}_{j \notin a \cap j \in active} w_{j,n,t}}{\sum_{j=i}^{J} \mathbb{1}_{j \notin a \cap j \in active}} \\
&+ \beta_3 \cdot \frac{\sum_{j=i}^{J} \mathbb{1}_{j \in a \cap j \in passive} w_{j,n,t}}{\sum_{j=i}^{J} \mathbb{1}_{j \in a \cap j \in passive}} \\
&+ \beta_4 \cdot \frac{\sum_{j=i}^{J} \mathbb{1}_{j \notin a \cap j \in passive} w_{j,n,t}}{\sum_{j=i}^{J} \mathbb{1}_{j \notin a \cap j \in passive}} \\
&+ \beta_5 \cdot w_{SMCCF,n,t} + \beta_6 \times \mathbb{1}_{i \in \text{BlackRock},t} + \beta_7 \cdot w_{SMCCF,n,t} \times \mathbb{1}_{i \in \text{BlackRock},t} \\
&+ \gamma_{\mathbf{1}} \cdot \mathbf{controls_{i,t}} + \gamma_{\mathbf{2}} \cdot \mathbf{controls_{n,t}} + \delta_t + \delta_i + \epsilon_{i,n,t}
\end{aligned}
$$

where $w_{SMCCF,n,t}$ is the weight of corporate bond n in the SMCCF portfolio in quarter t and $\mathbb{1}_{i \in \text{BlackRock},t}$ is an indicator variable equal to one if the insurance company i is advised by BlackRock in quarter t. Table 5 shows the results of this regression. The coefficients of $\beta_1, \beta_2, \beta_3, and \beta_4$ are similar to those from specification 4, although their magnitude is larger after computing relative portfolio weights. The most interesting results relate to β_5, and β_7. β_5 measures the co-movement between insurers weights and the SMCCF portfolio. The coefficient is positive and highly significant suggesting that insurers portfolios strongly co-move with the SMCCF one. This is expected given that the Fed defined very specific criteria for the set of eligible bonds that the SMCCF could buy, most of which overlap with insurers criteria as well (e.g. no convertible or subordinated bonds, no equity-linked or structured securities) and capital requirements similar to those that insurers are also subject to (10% for assets in category I, that is investment grade, and 14.29% for category II, that is high yield).[11] In addition, this result confirms the findings from O'Hara and Zhou (2021) which provide evidence that both the SMCCF and insurers were providing liquidity by purchasing corporate bonds during the Covid-19 liquidity crisis. β_7 is also positive and statistically significant. This indicates that insurance companies that are advised by BlackRock are even more likely to purchase the assets that are also acquired by the SMCCF. This result is consistent with the theory of economies of scale.

6 Conclusion

This paper studies the presence of external advisers in the life insurance industry. I construct a novel dataset by relating the life insurers advisers with the mutual fund advisers in the CRSP mutual fund database. When I compare insurers and mutual funds corporate bond portfolios, I find that portfolios

[11] For more information on the institutional details of the SMCCF, see the Investment Management Agreement.

Table 5: Portfolio weights on BlackRock portfolio weights and mutual fund portfolio weights

	Dependent variable: weight
	(1)
β_1	-2.281
	(1.881)
β_2	-91.912***
	(7.066)
β_3	0.082
	(5.935)
β_4	9.640***
	(2.224)
β_5	30.876***
	(8.737)
β_6	-0.020
	(0.012)
β_7	35.961**
	(18.287)
Observations	695640
Company FE	Yes
Quarter FE	Yes
Company controls	Yes
CUSIP controls	No
N. of groups	594
Note:	*p<0.1; **p<0.05; ***p<0.01

of investors advised by the same firm tend to be more similar to each other in the cross section. In particular, I find that insurers portfolios advised by the same firm are 3 times more similar than portfolios of unrelated insurers. I also find that insurers and mutual funds portfolios advised by the same firm are more similar than those of unrelated ones. This evidence suggests that there could be economies of scale at play in the corporate bond market, where advisers could purchase the same bonds for their multiple investors in order to decrease the transaction costs. However, when I study the source of variation of portfolio weights, I notice that the similarity disappears after controlling for both insurer and corporate bond characteristics. Given that the analysis on portfolio similarity is intrinsically endogenous, I use the Covid-19 liquidity crisis as an exogenous shock in order to study whether insurance companies portfolios advised by BlackRock respond to the very rapid and deterministic expansion of the SMCCF portfolio. Given that the Fed provided BlackRock with a very strict mandate on how to manage the facility, it is unlikely that BlackRock investment decisions for the SMCCF were conditioned by the portfolio decisions of the insurance companies that BlackRock advised. At the same time, I show that insurance companies investments were likely affected by the investments from the SMCCF. In particular, I show that insurers advised by BlackRock were much more likely to purchase the same bonds as the SMCCF. This result, provides strong suggestive evidence of the fact that when facing large inflows, advisers may combine purchase identical assets for their clients, thus leveraging on economies of scale in the corporate bond market.

References

Becker, B. and V. Ivashina (2015, September). Reaching for yield in the bond market. *The Journal of Finance 70*(5), 1863–1902.

Becker, B., M. M. Opp, and F. Saidi (2021, September). Regulatory forbearance in the u.s. insurance industry: The effects of removing capital requirements for an asset class. *The Review of Financial Studies 35*(12), 5438–5482.

Boyarchenko, N., C. Cox, R. K. Crump, A. Danzig, A. Kovner, O. Shachar, and P. Steiner (2022). The primary and secondary corporate credit facilities. *SSRN Electronic Journal*.

Brown, K. C., W. V. Harlow, and L. T. Starks (1996, March). Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *The Journal of Finance 51*(1), 85–110.

Chevalier, J. and G. Ellison (1997, December). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy 105*(6), 1167–1200.

Chodorow-Reich, G., A. Ghent, and V. Haddad (2020, May). Asset insulators. *The Review of Financial Studies 34*(3), 1509–1539.

Dickerson, A., P. Mueller, and C. Robotti (2023, November). Priced risk in corporate bonds. *Journal of Financial Economics 150*(2), 103707.

Edwards, A. K., L. E. Harris, and M. S. Piowar (2007, May). Corporate bond market transaction costs and transparency. *The Journal of Finance 62*(3), 1421–1451.

Ellul, A., C. Jotikasthira, and C. T. Lundblad (2011, September). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics 101*(3), 596–620.

Girardi, G., K. W. Hanley, S. Nikolova, L. Pelizzon, and M. G. Sherman (2021, October). Portfolio similarity and asset liquidation in the insurance industry. *Journal of Financial Economics 142*(1), 69–96.

Goldstein, I., H. Jiang, and D. T. Ng (2017, December). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics 126*(3), 592–613.

Harris, L. E. and M. S. Piwowar (2006, May). Secondary trading costs in the municipal bond market. *The Journal of Finance 61*(3), 1361–1397.

Huang, J., K. D. Wei, and H. Yan (2007, May). Participation costs and the sensitivity of fund flows to past performance. *The Journal of Finance 62*(3), 1273–1311.

Ippolito, R. A. (1992, April). Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. *The Journal of Law and Economics 35*(1), 45–70.

Kim, K., J. T. Leverty, and J. T. Schmit (2023). The effects of investment advisers in the life insurance industry. *SSRN Electronic Journal*.

Knox, B. and J. A. Sørensen (2023). Asset-driven insurance pricing. *SSRN Electronic Journal*.

Koijen, R. S. J. and M. Yogo (2022, September). New perspectives on insurance. *The Review of Financial Studies 35*(12), 5275–5286.

Lynch, A. W. and D. K. Musto (2003, September). How investors interpret past fund returns. *The Journal of Finance 58*(5), 2033–2058.

Niehaus, G. (2016, November). Managing capital via internal capital market transactions: The case of life insurers. *Journal of Risk and Insurance 85*(1), 69–106.

O' Hara, M., Y. Wang, and X. (Alex) Zhou (2018, November). The execution quality of corporate bonds. *Journal of Financial Economics 130*(2), 308–326.

O'Hara, M. and X. A. Zhou (2021, October). Anatomy of a liquidity crisis: Corporate bonds in the covid-19 crisis. *Journal of Financial Economics 142*(1), 46–68.

Schultz, P. (2001, April). Corporate bond trading costs: A peek behind the curtain. *The Journal of Finance 56*(2), 677–698.

Sen, I. (2022, October). Regulatory limits to risk management. *The Review of Financial Studies 36*(6), 2175–2223.