Cash-Flow Risk Management in the Insurance Industry: A Dynamic Factor Modeling Approach

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Introduction

This project models cash-flow risks and empirically analyzes cash-flow risk management of insurance firms under a dynamic factor modeling framework, which can capture the dynamic interactions between an insurance firm's activities in financing, investing, underwriting, and risk transferring. In addition, through the use of a factor-augmented autoregressive (FAAR) technique, the empirical analysis can simultaneously consider the effects of macro-factors that are common to the entire economy as well as those factors specific to the insurance industry.

Cash is king. It is true for entrepreneurs, and it is also true for managers of financial institutions. Cash-flow risks have long been one of the most essential factors while managing a variety of risks, particularly for the insurance industry, which faces unique underwriting risks not observed in other industries. To the insurance industry, cash flows can be generated through underwriting activities, financing and investing choices, and even managing risks; consequently modeling cash-flow risks will be on a dynamic basis process because it is essential to forecasting and managing financial and underwriting risks.

To model the cash-flow risks specific to the insurance industry, we have to capture the dynamics of the cash-flow–generating process of an insurer. The cash-flow–generating process can be characterized by two major components: (1) the earnings that result from core activities and cannot be modified and (2) other profits that can be modified through the dimensions of investment choices, risk management, and financial policies. In addition, the factors underlying the cash-flow–generating process may be intertwined and thus under the generating process can present the risks to the extent of cash-flow level. For instance, the downside risk of a company can be signaled by an abnormal decrease in operating cash flows. Moreover, the discrepancy of the magnitude and timing of the cash flows generated from underwriting insurance policies and those generated from investment activities create cash-flow uncertainty and risks to insurance firms.

For insurance firms, cash flows generated from investment, underwriting, and risk management activities are important indicators in financial management and are the key variables in capital budgeting decisions. Hence, these generated cash flows will provide internally interacting feedback on determining the insurers' strategies of underwriting, risk management, and investment from time to time. Correspondingly, cash-flow processes and cash-flow risks demonstrate their dynamic characteristics.

This study investigates management of cash flows by the insurance industry by incorporating its interactions with risk management and investment management after identifying and capturing the dynamic relationships between one another. For example, an efficient implementation of a risk management mechanism can mitigate agency costs deriving from overinvestments of free cash flows. In addition, a well-established investment portfolio can efficiently utilize free cash flows for better asset allocation. Furthermore, we extend the research to explicitly consider the dynamic effects of economy-wide macro-variables and industry-wide common factors. The research sample, based on the insurance industry, provides an opportunity to incorporate the factors uniquely specific to this industry, namely, insurance underwriting cycles and regulatory requirements, into the model. Therefore, this study conducts a comprehensive analysis of cash-flow modeling and cash-flow risk management in the insurance industry.

The existing literature provides evidence that suggests the relationships between cash flows, investment, and risk management. As demonstrated in Alti (2003), cash flows contain valuable information about a firm's investment opportunities. In addition, Almeida et al. (2004)

identify the significant relationship between cash-flow sensitivity and financial constraints. Rochet and Villeneuve (2011) examine how risk management mechanisms interact with the uncertainty of cash-flow levels and conclude that the decisions are simultaneously endogenous. In addition, the literature has shown that insurers have more actively participated in the derivative markets by employing financial derivatives not only to smooth cash-flow uncertainty from their invested assets and underwriting liabilities but also to generate more cash flows. Therefore, cash-flow management is important in the field of risk management, particularly for the insurer firms who intend to reach effective asset/liability duration management. To the best of our knowledge, very few of the existing studies have addressed the issues of cash-flow risk management of insurers under the framework of considering the dynamic risk management in investing, financing, and underwriting.

In this project we apply dynamic factor modeling (Stock and Watson 2006, 2009) to capture the dynamic interactions between risk management and investment management by incorporating economy-wide macro-variables and industry-wide business cycle variables. Moreover, to further empirically carry out the applications of dynamic factor modeling as suggested in Rochet and Villeneuve (2011), we utilize a factor-augmented autoregression model (FAARM) through which we model how cash flows respond to the dynamic interactions mentioned above to explicitly model the nonmonotonic effects. The research by Born et al. (2009) and Lin et al. (2011) explores the dynamic interactions between risk management and financial management in the U.S. property and liability insurance industry, but the explicit effects on cash-flow management are left for future research in their study. As financial intermediaries, the insurance industry is subject to various sources of risk, including interest rate risk, market risk, credit risk, and liquidity risk. Engaging in investment activities is one major source that generates the risks mentioned above, and the variability of cash flows reflects a firm's risks (Keown et al. 2007; Shin and Stulz 2000). All risks, particularly liquidity risk, are related to cash flows. Bakshi and Chen (2007) concluded that investing in stocks leads to the cash flows embedded with higher risks. Ballotta and Haberman (2009) and Azcue and Muler (2009) specifically examine the investment strategies of insurance companies and emphasize minimizing the default risks of the insurers, but not the dynamic optimal investment strategies of insurers over economic downturns. In other words, they estimate the credit risk or liquidity risk at the firm level but fail to consider the macroeconomic issues such as interest risk and market risk. The study by Wen and Born (2005) explores the dynamic interactions between investment strategies and underwriting cycles, and their study suggests that although one may investigate how insurers dynamically adjust their investment and hedging strategies, the dynamic interactions between asset and liability risks corresponding to the underwriting cycles should be taken into consideration.[1]

Taken with these earlier studies, our study intends to bridge the extant literature by taking steps further to model the cash-flow risks by taking into account the uncertainty of the market cycles, thereby explicitly examining insurers' cash-flow management. Using the highly regulated insurance industry as a research sample enables us to further extend the existing literature by incorporating the specific industry-wide characteristics, such as regulatory requirements and underwriting cycles, in the models. The simultaneous consideration of market cycle, underwriting cycle, and regulatory requirements enables us to fully depict the insurance firms' investment, risk management, and underwriting strategies.

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[1] As suggested by Fairley (1979), expected earnings to be realized at the end of a policy year consist of the underwriting profit margin and investment returns; this highlights the importance of considering the interactions between investment and underwriting activities.

This study, by taking into account the different phases of market cycles, provides a thorough examination of insurers' investment and hedging strategies in each phase (e.g., market upturn or downturn) of a cycle from the stage of including conventional investments to the stage of including the innovative financial derivatives as investment and hedging tools. Thus, we will draw a conclusion on how the inclusion of hybrid assets (for hedging and investment) can expand insurers' investment portfolios and in addition can dynamically adjust insurers' investment strategies as they face market downturns. Through the application of dynamic financial modeling (DFM), the dynamic adjustment between investment, underwriting, and hedging strategies corresponding to different phases of cycles (market cycle and underwriting cycle) can be captured.

Methods

Cash-Flow–Generating Process

Based on Rochet and Villeneuve (2011), we modify the cash-flow–generating process dC_t for an insurer, which can be characterized as

$$dC_t = (\mu dt + \sigma dW_t) + r_t C_t dt + (\sigma_R dW_{Rt} - L dP_t) - dZ_t + (dI_t - dV_t), \quad (1)$$

where $(\mu dt + \sigma dW_t)$ corresponds to the underwriting profits of an insurance firm: μ is the expected profitability per unit of time, σ is the volatility of ''primary'' earnings, and W_t a standard Wiener process, which cannot be hedged or insured. We use r_t as the rate of return generated from investment through asset allocation or from derivative use for income generation; hence, $r_t C_t dt$ is the investment cash inflows. Here $(\sigma_R dW_{Rt} - L dP_t)$ corresponds to the risks that can be managed through the use of either financial derivatives or reinsurance. Z_t is the (nondecreasing) cumulative payout process, I_t is the additional funds accumulated through financing by issuing securities, and V_t is the corresponding financing costs.

The cash-flow–generating process shown in equation (1) demonstrates that for an insurance firm, cash-flow management involves underwriting, investing, financing, and risk-transferring management. Nevertheless, it is not easy to estimate equation (1) in practice since the empirical model should contain more variables than those in equation (1). Henceforth, we extend the dynamic factor modeling by following Almeida et al. (2004) to dynamically estimate the cash flows' sensitivity to financial constraints. The DFM considered in this study is a dimension-reduction technique that incorporates more information in the calculation and thus is able to depict the dynamic patterns of cash flows of an insurance company.

Dynamic Factor Modeling

Dynamic factor modeling (DFM) is being more frequently applied by policymakers and economic researchers for forecasting purposes by considering the key macroeconomic variables. To the best of our knowledge, this project is the first study to apply DFM in the insurance industry to describe firm-level cash-flow volatility with the consideration of macro-variables and factors uniquely specific to the insurance industry, namely, regulatory requirements and underwriting cycles. Stock and Watson (2002), Forni et al. (2005), and Kapetanios and Marcellino (2004) conclude that DFM can be applied to extract common factors. From the model, all or a subset of the estimated factors can be empirically carried out through the utilization of regression models for prediction purposes.

Specifically, DFM was developed by Geweke (1977) and further revised by Giannone et al. (2004) and Watson (2004). Although DFM is an extension of factor analysis, it can depict a time-varying nature by considering the dynamic patterns of factor analysis. As a result, we are able to apply DFM to incorporate macro-common factors (such as underwriting cycles specific to the insurance industry and macroeconomic variables to all industries) as well as firm-specific features in modeling cash flows. In addition, the application of DFM can solve the multicolinearity problem when too many variables are considered in a regression function (see Sargent and Sims 1977, among others). Moreover, as we incorporate macro-business cycles and underwriting cycles in the analysis, it is likely to observe structural changes along with the presence of cycles. The application of DFM enables us to explicitly depict the structural changes embedded in business cycles while theoretically modeling the factors and empirically analyzing the data (Sargent and Sims 1977; Belviso and Milani 2006).

Stock and Watson (2005) propose the factor forecasting model, in which the factors are constructed by using predictors in the following dynamic structural equation:

$$X_t = \Lambda F_t + e_t \qquad (2)$$

where X_t contains N observable variables, F_t is the estimated unobservable latent factors, Λ is the factor-loading matrix, and e_t is the error term. In other words, X can be explained by F through the estimation of factor loadings. In particular, F_t includes both firm- and industry-level factors. The firm-level factors contain the latent variables related to insurers' activities in underwriting, investing, and derivatives usage, and the industry-level factors include the latent variables related to the macro-variables as well as industry-specific variables, namely, regulatory requirements and underwriting cycles. The dynamic interactions are captured through the factor loading Λ and are therefore reflected in X_t; they explicitly describe the observed derivative usage, investment asset allocation, and insurance underwriting. In sum, based on dynamic factor modeling, the dynamic interactions between derivatives utilization, investment asset allocation, and underwriting are captured in equation (2) by incorporating macro- as well as firm-specific variables. The DFM model applied in this study distinguishes itself from previous literature by the fact that the model does not require strong assumptions on the objective function, such as firm value maximization or total cost minimization, which are discussed in the literature associated with cost or profit efficiency (Cummins et al. 1999; Cummins and Weiss 2000; Cummins and Xie 2008).

Integrating a cash-flow–generating process into the dynamic cash-flow model, a FAARM can be developed as an equation by considering not only cross-sectional characteristics, but also time-series factors. In light of Almeida et al. (2004), we apply the model in equation (3) to depict how cash flows are shown after the aforementioned interactions are simultaneously taken into consideration:

$$C_{t+1}^{1} = \alpha + \gamma' F_t + \Phi(L) C_t + u_{t+1}, \qquad (3)$$

where C_{t+1}^{1} is the one-period forecast cash flow at time *t*, F_t is the estimated unobservable factors from equation (2), $\Phi(L)C_t$ is the lagged cash flows at time *t*, and u_{t+1} is the random error for the estimated dependent variables. This model can be further carried out for empirical applications. Based on the model setup, we extend this functional process to a measurable system that can capture the dynamic interactions and draw an equilibrium/optimal status for risk management investment and underwriting strategies. The estimation results $\hat{F}_T$ from equation (2) along with equation (3) enable us to derive the empirical autoregression model (FAARM) described in equation (4):

$$\hat{C}_{T+1|T}^{FAAR,1} = \hat{\alpha} + \hat{\gamma}' \hat{F}_T + \hat{\phi}_T(L) C_T. \qquad (4)$$

Data

To carry out the applications of dynamic factor modeling for an explicit and comprehensive examination of insurers' cash-flow management, this study conducts an empirical analysis by employing the data pertaining to derivative transactions and the data related to insurers' underwriting, investment, and financing activities. In particular, we gathered data through access to a subscribed insurance database of *SNL Financial* that provides statutory financial data for the property and liability insurance industry. Through the utilization of *SNLxl*, we chose the data from prebuilt insurance templates, such as assets, liabilities, investment portfolios, cash flows, income statements, and derivatives transactions (Schedule DB). We collected quarterly data over the period 2001–2012 to ensure the feasibility of a time-series model with sufficient observations over periods.

In particular, the data collected are to identify insurers' underwriting, investing, and financing. In addition, the variations of cash flows as well as firm characteristics are retrieved. Furthermore, to incorporate the macro-factors into analysis, we include the macro-variables pertaining to economic growth, interest rate, inflation rate, and unemployment rate. We retrieved these macro-variables from *Economic Research & Data,* compiled by the Federal Reserve Board.[2] We require an insurer with nonnegative assets and premiums written in each quarter to be included in the sample. The data collection gives us a total of 1,275 firms to perform the dynamic factor model including the firm-level variables and macroeconomic variables that capture economic cycles.

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[2] http://www.federalreserve.gov/econresdata/default.htm.

This sample enables us to conduct principal components analysis and apply a dynamic factor time-series model for each of the 1,275 firms over the 48-quarter time period to make induction through the empirical results.

For brevity, in the following sections, we first use one randomly selected firm to conduct the analyses and employ the results from this firm to illustrate the feasibility and applicability of the models. Furthermore, we conduct subgroup analyses by categorizing the entire sample of 1,275 firms based on firm size into three subsamples: large-firm, medium-firm, and small-firm groups. Empirical results from the entire group and subgroup analyses enable us to infer the feasibility of applying DFM proposed in this study in forecasting cash flows and thus managing cash-flow risks in the insurance industry. [3]

Variable Construction

To empirically carry out the applications of FAARMs to manage cash flows through forecasting, we utilize equation (2) as the first step to identify the main principal components: the latent variables denoted by F_t through the observed variables, X_t. The second step is to incorporate the variables depicting the principal components identified through significance comparison from the first step's analysis to predict future cash flows. In particular, through the principal component analysis, which explains the cash-flow variables related to underwriting, investing, financing, and risk-managing activities, the generated principal components are culled as the main factors and are incorporated in equation (4) along with an autoregression model to forecast the cash flows of the next period. Cash flow (*CF*) is the main variable involved in each step of

[3] The dynamic factor models developed can be empirically applied to the insurance industry of life or property-liability (P-L). At this stage, with the limit of data access, the current study utilizes the data collected from the P-L insurance companies to demonstrate the effectiveness of DFM empirical applications.

model application and estimation. To infer comparable results among firms, we construct a normalized CF variable, $\ln(CF_{i,t} - \min(CF_{i,t}))$. It is constructed by taking the logarithm of the difference of the cash flows of firm i at time t ($CF_{i,t}$) and the minimal cash flow among all observations ($\min(CF_{i,t})$).[4]

The time-series model estimation calls for the unit root test to infer an appropriate order for an autoregression model (AR), and the results suggest a first-order autoregression model, *AR(1)*, that is more appropriate based on the principle of root mean square error (RMSE) minimization. The application of a dynamic factor model is carried out by incorporating this AR(1) model along with the principal components derived from step (1), namely, AR(1) + $\sum_{k=1}^{j} PC_k$, in which the optimal number of principal components (*PC*) can also be determined through the minimization of the RMSE of the model.

In terms of the choice of those observed variables X_t in equation (2), we follow the analysis of Born et al. (2009) and categorize the variables mainly pertaining to (1) capital management, (2) investment and financial management, and (3) risk management. In addition, we choose the variables capturing insurers' firm characteristics and their underwriting activities as well as the macroeconomic environment. The variables in each category depict different risk factors of an insurance firm. Table 1 summarizes the variables under study in the first step (equation [2]) of an FAARM.

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[4] We follow the conventional method applied in the study of the profit frontier to normalize the key variable.

Table 1 Definitions of the Variables Utilized in the Model

Capital Management Variables	
Cap_AT	Capital/surplus to asset ratio
Leverage	Ratio of liability to total assets
Firm Characteristics Variables	
Size	Natural logarithm of the total assets
IT_R	Ratio of computer and equipment (quarterly report: electronic data processing equipment and software)
Investment (Financial) Management Variables	
Bd_R	Bond investment to total assets ratio
PStk_R	Preferred stock to total assets ratio
CStk_R	Common stock to total assets ratio
Mtg_loan_R	Mortgage loans on real estate to total assets
RealE_R	Real estate to total assets ratio
Sterm_R	Short-term investment to total assets ratio
LTerm_R	Long-term investment to total assets ratio
Risk Management Variables	
Deri_R	Ratio of derivatives to total assets
ReInsAsset_R	Ratio of reinsurance premium written to total premium written
Underwriting Activities Variables	
NetPremRec_R	Net premium ratio
UW_R1	Underwriting gain (loss) to total assets ratio
NPW_GPW	Ratio of net premium written to gross premium written
Macroeconomic Variables	
Growth	Economic growth rate based on U.S. GDP
Interest rate	10-year Treasury bond yield
Unemployment	U.S. unemployment rate
Inflation	Inflation rate based on U.S. CPI

Empirical Results

In the empirical analyses, for each individual insurance firm, we have conducted a time-series analysis for the 48 quarters for the period 2001–2012. Consequently we come up with time-series results for 1,275 firms with feasible data. It is essential to find means to better categorize these sample firms based on common features. In this study, we use firm size as a basis to categorize firms into different groups and conduct the analyses for (1) the entire group, (2) a large-firm group, (3) a medium-firm group, and (4) a small-firm group. To better illustrate the procedures of applying the model, we base our study on a randomly selected firm to present the results of each step of the DFM application. The results provide us with evidence supporting the accessibility and applicability of the DFM model for its forecasting power of cash flows.

Principal Components Results

The time series analysis incorporating equations (2) and (3) is carried out in this section. We illustrate the empirical results of the principal component analysis with a selected typical firm, C1. The results are shown in Table 2. Since the model is performed based on a standardized data set, the value of the estimated coefficient for each variable describes how much that variable contributes to the principal component. In Table 2 we indicate the coefficients that are larger than 0.20 (Franklin et al. 1995) with an asterisk sign to indicate its comparative significance to other variables and investigate the patterns of each principal component.

As shown in Table 2, principal component 1 (PC1) is more related to the variables in the categories of capital, investment, and risk managements through the magnitudes of the corresponding coefficients. For example, the capital ratio variable (Cap_AT) has a coefficient 0.2797, whereas the preferred-stock (PStk_R), real estate investment (RealE_R), and the risk management variable of the derivative ratio (Deri_R) all have a larger coefficient, 0.3280, than the others.

For principal component 2 (PC2), it can be depicted by the following significant variables: capital ratio (Cap_AT), IT ratio (IT_R), short-term investment ratio (STerm_R), and reinsurance ratio (ReInsAsset_R). In other words, PC2 pertains to insurers’ capital management, investment management, risk management, and underwriting activities. In addition, among the macro-variables, interest rate and unemployment rate present significant but contrasting effects illustrating PC2. On the other hand, for principal component 3 (PC3), the variables pertaining to the insurer's underwriting activities and investment management are more significant to describe PC3. In particular, underwriting gain (UW_R1) has a significant coefficient with value 0.4279, whereas the net premium ratio (NPW_GPW) shows a negative and significant coefficient, −0.3210. In addition for the investment activities, the investment in common stocks (CStk_R) is significant with a coefficient magnitude of 0.4753. Moreover, for principal component 4 (PC4), all three underwriting variables—net premium to assets ratio, underwriting gains, and net premium to gross premium written ratio—are significant and negatively associated with PC4.

Consequently, among the associations between the principal components and insurers' cash-flow management,[5] PC1 and PC2 are more relevant to capital, investment, and risk management, whereas PC3 and PC4 are relevant to investment management. In addition, PC2, PC3, and PC4 all pertain to underwriting activities, whereas PC4 presents a more significant association compared to PC2 and PC3.

To carry out the empirical application of DFM modeling, we first identify how a principal component can be associated with those observed variables in the categories of insurers in capital management, investment management, risk management, underwriting activities, and macro-factors. The results of a significant relation between principal components and observed proxy variables have demonstrated the feasibility of the measured model. For the next step in

[5] We utilize the number of significant variables in each category of cash-flow management to infer the corresponding association between principal components and proxy variables. For example, in the category of investment management, for PC1 and PC2, there are three significant variables. On the other hand, for PC3 and PC4, two of the variables are significant in this category.

applying DFM modeling, we incorporate the results from principal component analysis into autoregression cash-flow forecasting models (FAARMs) to further demonstrate the forecasting power of this model. Taken as a whole, this model enables insurers to forecast cash flow for the next time period and therefore further manage cash-flow risks.

Table 2
Empirical Result of Principal Component Analysis

	PC1	PC2	PC3	PC4
Capital management				
Cap_AT	0.2797[a]	0.2427[a]	-0.0538	0.1723
Leverage	−0.2797[a]	−0.2427[a]	0.0538	−0.1723
Firm characteristics				
Size	−0.3383[a]	0.0506	−0.0498	0.0018
IT_R	−0.1317	−0.4256[a]	−0.2105[a]	0.0874
Investment (financial) management				
Bd_R	0.2279[a]	0.2741[a]	−0.2920[a]	0.1225
PStk_R	0.3280[a]	−0.0706	0.0601	−0.1451
CStk_R	−0.1474	−0.1072	0.4753[a]	0.3106[a]
RealE_R	0.3280[a]	−0.0706	0.0601	−0.1451
Sterm_R	0.0059	−0.3387[a]	−0.1094	−0.2444[a]
LTerm_R	0.2574[a]	−0.2161[a]	0.1609	−0.1550
Risk management				
Deri_R	0.3280[a]	−0.0706	0.0601	−0.1451
ReInsAsset_R	−0.1932	−0.3205[a]	−0.0133	−0.1981[a]
Underwriting activities				
NetPremRec_R	−0.1832	0.2626[a]	0.1990	−0.3449[a]
UW_R1	0.1112	0.0321	0.4279[a]	−0.2505[a]
NPW_GPW	−0.0217	−0.0075	−0.3210[a]	−0.5514[a]
Macroeconomic variables				
Growth	0.0246	−0.1168	0.4770[a]	0.0251
Interest rate	0.1544	−0.3486[a]	−0.1283	0.2812[a]
Unemployment	−0.1801	0.3498[a]	0.0712	−0.2099[a]
Inflation	0.0297	−0.0197	0.0945	-0.0688

Note: Utilizing principal component analysis is the first step to carry out the application of DFM modeling through the combination of equations (2) and (3):

$$X_t = \Lambda F_t + e_t, \tag{2}$$

where X_t contains N observable variables. F_t is the estimated unobservable latent factors, Λ is the factor loading matrix, and e_t is the error term:

$$C^1_{t+1} = \alpha + \gamma' F_t + \Phi(L)C_t + u_{t+1}, \tag{3}$$

where C^1_{t+1} is the one-period forecast cash flow at time *t*, F_t is the estimated unobservable factors from equation (2), $\Phi(L)C_t$ is the lagged cash flows at time *t*, and u_{t+1} is the random error for the estimated dependent variables.
[a]The magnitude of the coefficient is larger than 0.20. See Table 1 for the definition of each variable.

Table 3
Empirical Results of FAAR (DFM) of Firm C1

	AR(1)		FAAR1		FAAR2		FAAR3		FAAR4		FAAR5	
	AR(1)		AR(1) + PC_1		AR(1) + $\sum_{j=1}^{2} PC_j$		AR(1) + $\sum_{j=1}^{3} PC_j$		AR(1) + $\sum_{j=1}^{4} PC_j$		AR(1) + $\sum_{j=1}^{5} PC_j$	
	Coefficient	*t* value	Coefficient	*t* value	Coefficient	*t* value	Coefficient	*t* value	Coefficient	*t* value	Coefficient	*t* value
Constant	2.74552	3.77***	2.84106	3.89***	4.56867	5.11***	4.56316	5.02***	4.92116	5.62***	4.92096	5.55***
$\ln CF_{(t-1)}$	0.54789	4.56***	0.53216	4.42***	0.24766	1.68*	0.24857	1.66	0.18962	1.32	0.18965	1.30
PC1			0.00005	1.18	0.00006	1.50	0.00006	1.48	0.00006	1.58	0.00006	1.56
PC2					0.00021	2.94***	0.00021	2.89***	0.00024	3.32***	0.00024	3.28***
PC3							−0.00001	−0.06	0.00000	−0.02	0.00000	−0.02
PC4									−0.00020	−2.38**	−0.00020	−2.35**
PC5											0.00000	0.01
R^2	0.3163		0.3372		0.4481		0.4482		0.5151		0.5151	
RMSE	0.00079		0.00078		0.00072		0.00073		0.00069		0.00070	
R^2 change[a]			6.61%		32.89%		0.02%		14.93%		0.00%	
RMSE change[b]			−1.27%		−7.69%		1.39%		−5.48%		1.45%	

Note: This is the second step in carrying out the application of the FAARM through equation (4):

$$\hat{C}_{T+1|T}^{FAAR,1} = \hat{\alpha} + \hat{\gamma}'\hat{F}_T + \hat{\phi}_T(L)C_T, \qquad (4)$$

where the estimation results $\hat{F}_T$ are obtained from equations (2) and (3) in the first step.

[a] R^2 change is defined as the percentage of the R^2 increase as one more principal component is included in AR; i.e., $\{R^2[AR(1) + \sum_{j=1}^{k+1} PC_j)] - R^2[AR(1) + \sum_{j=1}^{k} PC_j]\}/\{R^2[AR(1) + \sum_{j=1}^{k} PC_j]\}$.

[b] RMSE change is defined as the percentage of RMSE decrease as one more principal component is included in AR; i.e., $\{RMSE[AR(1) + \sum_{j=1}^{k+1} PC_j)] - RMSE[AR(1) + \sum_{j=1}^{k} PC_j]\}/\{RMSE[AR(1) + \sum_{j=1}^{k} PC_j]\}$. ***, **, and * denote the significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Illustrations of FAAR (DFM) Applications

To empirically demonstrate the applications of DFM, we first use one selected sample firm to illustrate the second step of utilizing a different number of principal components into autoregression to infer DFM and evaluate its forecasting power. Tables 3 and 4 summarize the results based on that single selected firm. Following similar procedures, we apply DFM to the entire sample of 1,275 firms and the subgroups of entire the sample categorized by firm size.[6]

Table 3 shows the empirical results of FAARMs incorporating a different number of principal components derived from step 1 through the autogression model, namely, AR(1) + $\sum_{j=1}^{k} PC_j$, where k is an optimum number of principal components to be determined via comparison of root mean square error (RMSE). Mathematically, the more PCs that are involved in the model, the higher the R^2 is expected to be, and the more acute forecasting the model can accomplish. Nevertheless, although the inclusion of an additional principal component may significantly increase the model's accuracy, it is not necessary to increase the number of PCs included in the model. We implement five FAARMs, namely, FAAR 1: AR1 + one principal component, FAAR 2: AR1 + two principal components, … , FAAR 5: AR1 + five principal components.

In addition, as indicated in Table 3, among the five FAARMs, the models including the second PC (PC2) and the fourth PC (PC4) consistently show their significance (at least at the 5

[6] For each individual firm in the entire sample, we conduct the same analyses as described in Tables 2 and 3. It is unnecessary to present all the results for all 1,275 sample firms. The results presented are based on a summary of the analyses for all 1,275 firms.

percent level).[7] Referring to the first step of FAARM as shown in Table 2, the second PC is featured by its significant relation with capital management through the opposite relations with capital ratio and leverage, with investment risk through bond investment (Bd_R) and short-term and long-term investment (Sterm_R, Lterm_R), and with risk management through reinsurance, underwriting activities, and macroeconomic risk (interest rate and unemployment rate). On the other hand, the fourth PC (PC4) tends to be linked to all the proxy variables representing underwriting activities: NetPremRec_R, UW_R1, and NPW_GPW. PC4 also links to investment management through common stock (CStk_R) and short-term investment (Sterm_R), to risk management through reinsurance utilization, and to macroeconomic risk (interest rate and unemployment rate).

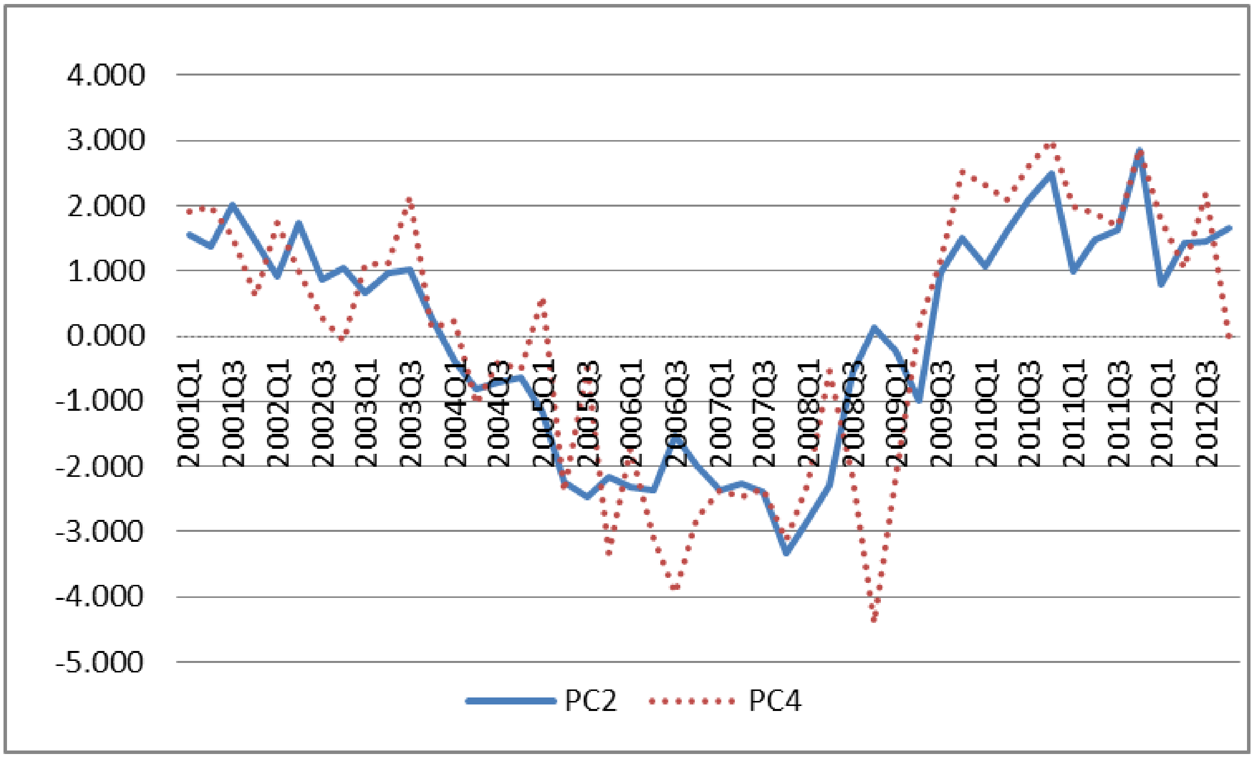
In particular, the time-varying movements of the second and the fourth PCs are depicted in Figure 1, which shows the cyclical characteristics. The approximate long-run paths of both PCs decrease after year 2001 and bounce back after 2008. This pattern shows that these two PCs are related to the macroeconomic risk, which decreases first and then increases, which coincided with the overall trend of risk in the environment of all the financial markets. We conjecture that the decrease in risk after 2001 may be caused by the adoption of the Sarbanes-Oxley Act, and the increasing pattern after 2008 signals the advent of the subprime mortgage crisis. The small variation of the second PC may represent the investment cycle. The variation for the fourth PC may indicate the insurance underwriting cycle due to the fact that the underwriting variables (NetPremRec_R, UW_R1, NPW_GPW) are more significant and important factors in the composition of the fourth PC. In Figure 1, the macroeconomic variables demonstrate the biggest

[7] As shown in Table 3, adding PC5 is insignificant in the estimation, and therefore it is not reported in Table 2 to save space.

waves, going downward after 2001 and then upward during and after 2009, whereas the underwriting variables may represent a smaller cycle around the patterns of macroeconomic variables.

Figure 1

Cyclical Patterns of Principal Components of the Sample Firm



Note: PC 2 is the estimated second principal component, and PC4 is the fourth principal component of the sample firm. They are the only two significant principal components out of five.

Table 3 also shows the R^2 and RMSE for each model and the relative changes from including one additional principal component. As shown in the table, RMSE of the model decreases from 0.00078 to 0.00072 when the model increases the number of principal components from one to two with the relative change of 7.69 percent. In addition, the inclusion of PC2 shows significance at the 1 percent level with the coefficient of 0.00021. The model shows another significant increase in R^2 and a decrease in RMSE as the model includes four PCs compared to three PCs. Moreover, in the AR(1) + $\sum_{j=1}^{4} PC_j$ model, PC2 and PC4 both show significant effects on forecasting the next period cash flow. Although the model increases the number of principal components from four to five, no decrease in RMSE or significant increase is observed in R^2. As a result, for this sample firm, we conclude that the FAARM with four principal components can best forecast the cash flows for the next period.

Table 4 illustrates the steps of empirically applying the DFM model to forecast the cash flows for the fourth quarter of 2012 by using the observed variables in the third quarter of 2012. In addition, Table 4 demonstrates the forecasting power of this DFM model. Panel A reports the actual observed value for each variable defined in Step 1 (listed in Tables 1 and 2). Based on the results of principal component analysis, Panel B summarizes the estimated value of each principal component by incorporating the estimated coefficients derived from Step 1 (shown in Table 2). For the FAARM including four components along with the first order of the autoregression model, that is, AR(1) + $\sum_{j=1}^{4} PC_j$ as shown in Table 3, the forecast cash flows of the fourth quarter of 2012 along with the actual value of cash flows are reported in Panel C. As demonstrated, the absolute value of the forecasting error is about 0.000003 in the logarithm term, or equivalent to \$0.13 per thousand dollars of cash flow.

In sum, for this one sample firm, the empirical results from the applications of DFM provide evidence supporting the feasibility and applicability of the model. In addition, the model provides relatively strong forecasting power to estimate future cash flows.

Table 4

Forecasting Values of FAAR Model

Panel A: Observed Values 2012Q3		**Panel B: Cash Flows of 2012Q3 and Estimated PC**		**Panel C: Observed and Forecast Cash Flow**	
	Observed Value				
Cap_AT	0.3965	$\ln CF_{(t-1)}$	6.073528	Observed lnCF 2012Q4	6.073244
Size	5.5925	$\widehat{PC}1$	−2.9970	Forecast lnCF 2012 fourth quarter	6.073545
IT_R	0.0004	$\widehat{PC}2$	2.3686	Difference ($)	0.130436
Bd_R	0.5787	$\widehat{PC}3$	0.0363		
PStk_R	0.0030	$\widehat{PC}4$	−1.7100		
CStk_R	0.2401				
Mtg_loan_R	0.0000026				
RealE_R	0.0000077				
Sterm_R	0.0000026				
LTerm_R	0.0000026				
Deri_R	0.0000026				
ReInsAsset_R	0.0561				
NetPremRec_R	0.0013				
UW_R1	−0.0063				
NPW_GPW	1.1867				
Leverage	0.6035				
Growth	0.7676				
Interest rate	1.7200				
Unemployment	7.8000				
Inflation	0.4462				

Empirical Results of FAAR (DFM) for the Entire Sample

For each firm of the entire sample, we examine the baseline of autoregression (AR) model as well as the optimum number of principal components to be included in the AR model through the comparison of RMSE. It is not necessary to present the results for each of the 1,275 different firms.[8] In addition, because the coefficients of PCs may vary from firm to firm and the empirical results of FAAR may differ from firm to firm, we categorize these 1,275 sample insurers based on their firm size to make an induction for grouping. Through categorization, insurers can correspondingly conduct their cash-flow forecasting and management based on common models fitted to the specific category. In particular, based on the amount of total assets of each firm, we sort these 1,275 firms by a descending order and classify them by asset level as (1) large firms, (2) medium firms, and (3) small firms. Such a grouping results in a similar number of observations in each group, 400, 400, and 475 firms in large, medium, and small firm groups, respectively. The accomplishment of this categorizing analysis will contribute to the literature by providing a more general cash-flow forecasting model to the insurance industry.

[8] For each firm, two baseline models will be conducted, and the corresponding RMSE will be compared to determine an appropriate baseline model included in the FAARM. This will produce 1275×2 RMSEs and 1275×2 R^2. In the second step of performing the FAAR technique, the FAARM consists of the best baseline model along with an optimum number of principal components. The optimum number (n) of principal components based on RMSE will be determined by comparing the RMSE of at least ($n-1$) FAARMs with ($n-1$) principal components. As a result, it will generate about 1,275×n RMSEs and 1,275×n R^2.

Table 5

Comparison between Baseline Models: AR1 and AR2

	All Firms		Large Firms		Medium Firms		Small Firms	
	N*	%	N	%	N	%	N	%
AR2 beats AR1	698	54.75%	237	59.25%	227	56.75%	234	49.26%
AR1 beats AR2	571	44.78%	162	40.50%	171	42.75%	238	50.11%
Undecided	6	0.47%	1	0.25%	2	0.50%	3	0.63%
Total	1275	100%	400	100%	400	100%	475	100%

Note: The whole sample includes 1,275, firms, where 400 are classified as large firms, 400 are medium firms, and 475 are small firms. The features of firms are listed in the first column of the table, and the number of firms in each cell indicates how many firms have this feature within the sample or subsample. "AR2 beats AR1" means the RMSE of AR2 is smaller than that of AR1 for a specific firm, and "AR1 beats AR2" means the RMSE of AR1 is smaller than that of AR2 for a specific firm. "Undecided" means the RMSE of AR1 is very close to that of AR2.
**N* = number of firms in each category.

Table 5 highlights the results of RMSEs of AR1 and AR2 models for all 1,275 firms and the three subgroups categorized by firm size. Before adding any principal components, we first select a baseline model between AR1 and AR2 through comparisons of RMSE for AR1 and AR2.

For the entire sample of 1,275 firms, AR1 and AR2 are performed for each firm. Results show that 698 firms show that AR1 has a lower RMSE than that of AR2, whereas 571 firms show a lower RMSE for AR2. That is, for these 698 firms (54.75 percent), AR1 outperforms AR2 as the baseline model, whereas for the other 571 firms (44.78 percent), AR2 outperforms AR1.[9] Therefore, the AR1 model is chosen over AR2 as the baseline model for further analysis.

For the large firm group, we first perform the baseline models of AR1 and AR2 before adding any augmented principal components for each of the 400 large firms. As shown in Table 5, 59.25 percent of the large firms tend to have lower RMSEs if AR1 is applied, whereas it is about 40.50 percent of the firms identifying lower RMSE through AR2. Similarly, AR1 outperforms AR2 for 56.75 percent of the medium firms (227 out of 400). On the other hand, for

[9] For the rest of the six firms, the RMSE of AR1 is very close to that of AR2. Consequently no significant difference exists between AR1 and AR2.

the small firm sample, 49.26 percent (234 out of 475) of the firms show that AR2 with lower RMSEs is a better baseline model than AR1. As a result, we conclude that AR1 is an appropriate baseline model to predict cash flows with higher accuracy for large-firm and medium-firm subsamples. AR2 is an appropriate model for small firms.

Table 6

Results of FAARM: Number of Models That Outperform the Baseline Model

	All Firms		Large Firms		Medium Firms		Small Firms	
	N*	%	N	%	N	%	N	%
5 models beatAR1	420	32.94%	112	28.00%	127	31.75%	181	38.11%
At least 4 models beat AR1	634	49.73%	190	47.50%	200	50.00%	244	51.37%
At least 3 models beat AR1	768	60.24%	227	56.75%	241	60.25%	300	63.16%
At least 2 models beat AR1	883	69.25%	278	69.50%	270	67.50%	335	70.53%
At least 1 model beats AR1	1130	88.63%	398	99.50%	365	91.25%	367	77.26%
No model beat AR1.	145	11.37%	2	0.50%	35	8.75%	108	22.74%
Total	1275	100.00%	400	100.00%	400	100.00%	475	100.00%

Note: The whole sample includes 1,275 firms, where 400 are classified as large firms, 400 are medium firms, and 475 are small firms. The features of firms are listed in the first column of this table, and N indicates the number of firms with the above feature listed in the first column. “5 models beats AR1” means the RMSE of any one of the five models is smaller than that of the baseline AR1 model; “at least 4 models beat AR1” means the RMSEs of four to five models are smaller than that of AR1; “at least 3 models beat AR1” means the RMSEs of three to five models are smaller than that of AR1; “at least 2 models beat AR1” means the RMSEs of two to five models are smaller than that of AR1; and “at least one models beat AR1” means the RMSE of only one out of the five models is smaller than that of AR1.
*N = number of firms in each category.

As the FAARM consists of a baseline model along with principal components, after identifying AR1 as the baseline model, we next examine whether use of the FAARM can further improve forecasting power compared to the baseline models in terms of the corresponding RMSE. Without prespecifying the number of principal components added to the baseline model to form the DFM model, Table 6 summarizes the RMSE of AR1 and different DFM models. In particular, we identify the five DFM models by the number of principal components (PCs) included along with the baseline model: that is, AR1 + one PC, AR1+two PC,…, AR1 + five PC. As shown in Table 6, for the entire sample of 1,275 firms, about 32.94 percent of the entire sample can improve the forecasting power through applying any one of the five DFM models compared to AR1.[10] In other words, for these 420 firms (i.e., 32.94 percent of the entire sample), FAAR improves the forecasting no matter how many principal components are utilized. In addition, about 634 firms can apply at least four or all five of the DFM models to increase forecasting power compared to the utilization of simple AR1. That is, about 49.73 percent of the entire sample can improve forecasting by using four or five of the DFM models consisting of AR1 and principal components. [11] Furthermore, about 60.24 percent (or 768 firms) of the entire sample is able to improve forecasting by applying three, four, or five of the DFM models consisting of principal components. The number of firms that can employ two, three, four, or five of the DFM models outperforming the baseline model is about 883 or 69.25 percent of the entire sample. Last, for most of the sample, about 88.63 percent of the entire sample can apply at least one among these five DFM models and generate lower RMSE regardless of the number of principal components included. In other words, FAAR improves forecasting as long as principal components are considered. Results from Table 6 do not specifically suggest the number of principal components to be included in a FAARM to enhance model performance.

Similar results are also true for the subsamples of different firm sizes. In particular, for the large- and medium-firm subsamples, 99.5 and 91.25 percent, respectively, can apply FAAR to improve forecasting performance compared to the baseline model. Interestingly, when

[10] A standardized RMSE with value 1 is set up for the baseline model AR1. A model outperforms AR1 if its standardized RMSE is less than 1; otherwise AR1 outperforms the model.

[11] Note that no specific number of principal components is identified when such forecasting performance is compared.

comparing results across different subsamples, we find that in the small-firm subsample, 38.11 percent of firms are featured with better FAARMs with any different number of principal components. On the other hand, in the large-firm subsample, this number decreases to 28.00 percent. That is, the variation of cash flows in large firms is usually larger, and the quality of the explanatory variables is better. Therefore, it is possible to use fewer principal components to capture the variation of cash flows for large firms, whereas the models for small firms need more principal components to explain the variation of the dependent variable (cash flows).

Overall, results from Table 6 suggest that a baseline model along with principal components enables a FAARM to increase its forecasting accuracy. However, these results do not specify the number of principal components to be included in the FAARMs that can further reduce RMSE. Following the preliminary conclusions from one-sample results summarized in Table 3, we implement five FAARMs: FAAR 1: AR1 + one principal component, FAAR 2: AR1 + two principal components, … , FAAR 5: AR1 + five principal components; see Table 7. In addition, the choice of the number of principal components can rely on the analysis of eigenvalues.[12]

[12] Untabulated results suggest that as five principal components are incorporated, more than 70 percent of the variation of the cash flows of the same period is captured. Henceforth, it is not necessary to add more factors in the FAAR approach.

Table 7

Results of FAARM: Optimum Number of Principal Components

	All Firms		Large Firms		Medium Firms		Small Firms	
Model	Best	%	Best	%	Best	%	Best	%
FAAR1: (AR1+1PC)	174	13.65%	2	0.50%	32	8.00%	140	29.47%
FAAR2: (AR1+2PCs)	833	65.33%	397	99.25%	309	77.25%	127	26.74%
FAAR3: (AR1+3PCs)	165	12.94%	0	0.00%	30	7.50%	135	28.42%
FAAR 4: (AR1+4PCs	184	14.43%	0	0.00%	21	5.25%	163	34.32%
FAAR5 (AR1+5PCs)	294	23.06%	0	0.00%	31	7.75%	263	55.37%
Total	1275		400		400		475	

Note: The number in each cell represents the number and percentage of firms with that best model. For example, here 174 out of 1,275 firms are featured with FAAR1as the best model, which is 13.65 percent of the entire sample, 833 out of 1,275 firms (65.33 percent) are featured with FAAR2 as the best model, etc. Note that the summation of the percentages is not 100 percent because more than one best model may exist for a specific firm.

To further identify the optimum number of principal components incorporated in a FAARM, we conduct the five FAARMs for each firm. Results are summarized in Table 7, in which the RMSE of each corresponding model within a firm is compared. Consequently, within a firm, a best FAARM is identified by the minimum RMSE among the five FAARMs. In particular, similar to step 2 in applying FAAR (DFM) to the selected firm shown in Table 3, among all 1,275 firms, each model is performed for each of the 1,275 firms, and the corresponding RMSE and R^2 of each model can be obtained. After performing the five models for each firm and ordering the RMSE_j for firm *I*, $\text{RMSE}_{i,j}$ stands for the RMSE for firm *i* under model *j*, where *i* is from firm 1 to firm 1,275 and *j* is from model 1 to model 5. For firm *i*, the minimum of RMSE from model *j* can be identified.[13]

A forecasting DFM model is the combination of the baseline model AR1 and a different number of principal components. The optimum number of principal components is determined

[13] Note that the vertical summation of the number of firms in Table 7 is not 1,275 since there may be more than one best model within a firm.

by RMSE comparisons. We define FAAR1 as AR1 + one principal component, FAAR1 as AR1 + two principal components, …, and FAAR5 as AR1 + five principal components.

Table 7 shows that the RMSE of FAAR1, …, FAAR5 for each firm demonstrates that the inclusion of more principal components does not necessarily lower the corresponding RMSE. For the entire sample, FAAR3 is the best model for about 12.94 percent of this sample, and FAAR4 is the best for 14.43 percent of it. On the other hand, for the large-firm sample, neither FAAR3, FAAR4, nor FAAR5 can serve as the best model. Nevertheless, FAAR3, FAAR4, and FAAR5 are the best models for 7.50, 5.25, and 5.75 percent of the medium firms, respectively, and they are also the best models for 28.42, 34.32, and 55.37 percent of the small firms, respectively. It is worth noting that when the size of a firm is small, FAAR with more factors tends to be the best model. Nevertheless, as the baseline model includes three, four, or five principal components, they perform as the best models for more sample firms. For example, about 294 (23.06 percent) firms of the entire sample can acquire the best forecast cash flows through the application of FAAR5, that is, AR1 + five principal components. As we further explore the forecasting power of the FAARMs across different categories of firms with different sizes, for large and medium firms, FAAR2 (AR1+2PCs) is identified as the best forecasting model with the respective 99.25 and 77.25 percent of firms with minimum RMSE, while for small firms, the FAAR5 model (i.e., AR1 + five PCs) is found to be the best forecasting model by which 55.37 percent of the firms are modeled and forecast with minimum RMSE.

Conclusions

This study applies a novel dynamic factor model (FAAR) to explain and forecast the time-varying patterns of cash flows of U.S. insurance companies. A principal component approach is employed to capture the augmented factors to be utilized for forecasting. This forecasting model incorporates risk management, capital management, the underwriting cycle, financial (investment) management, and macroeconomic risk and provides a reduced-dimension estimation. We first described the cash-flow–generating process and theoretical model of cash flows and then measured the FAARM.

Results from the first step (principal component analysis) aid in determining the macroeconomic cycles and underwriting cycles. The importance of derivatives investments and stock investments can also be observed for each insurance firm. Results from the second step offer evidence supporting that the dynamic factor model (or FAARM) improves the in-sample forecasting by reducing RMSE. The incorporation of principal components can further decrease RMSE for a majority of firms. Results are consistent for the entire sample as well as for different subsamples. In addition, with expected stable cash flows, large firms tend to have better forecasting by utilizing fewer principal components. As we observe, FAAR2 for large firms dominantly outperforms (99.25 percent) all other models. This ratio decreases to 77.25 percent for medium firms and 26.74 percent for small firms. FAAR5 is the best model for small firms. Such results suggest that for smaller firms, it takes more principal components to explain the variation of cash flows. We expect that the findings from this study can contribute to the practice of forecasting cash flows. Since the firm size can be identified, the corresponding proposed DFM to the firm size can be consequently applied by the insurer to forecast cash flows. In addition, following the identification of the variation of cash flows from the forecasting models, an insurer can further apply different financial instruments to control and manage the variation of cash flows, that is, cash-flow risks.

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