DNB Working Paper
No. 612 / October 2018

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DeNederlandscheBank
EUROSYSTEEM

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 612

October 2018

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Pension Funds Interconnections and Herd Behavior

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This version: October 2018 [§]

ABSTRACT

We use a unique dataset on the governance structures of 191 Dutch pension funds to study the effect of interconnections on strategic investment decisions in alternative assets. The interconnections are determined through trustees, actuaries, or dominant asset managers who provide services to multiple pension funds. We use spatial econometrics and find that pension funds that are interconnected via actuaries or dominant asset managers change their strategic allocations in the same direction over time, which is in line with herding. The effect of interconnections can be sizable. A pension fund interconnected to two other pension funds through the same dominant asset manager will increase on average its allocation to alternative investments by 2.5 percent if both pension funds increase their allocation by 10 percent, all else being equal. Conversely, pension funds interconnected via trustees display independent strategic asset allocations. Interconnections facilitate the transfer of information. However, herding can lead pension funds to develop an alternative asset class portfolio that is not in line with their liability structure, size, or knowledge level.

JEL classification: G11, G23.

Key words: Herd Behavior, Pension Funds, Asset Allocation, Alternative Asset Classes, Spatial Econometrics, Interconnections

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[§]The authors thank the Belgian Financial Forum; our discussant Benjamin Peeters; and the DNB seminar series, Bart Bos, Jaap Bos, Damiaan Chen, Denis de Crombgrugghe, Jeroen Derwall, Paul Elhorst, Iman van Lelyveld, Rogier Otten, Antoon Pelsser, and Paulo Rodrigues for their helpful comments on various versions of this work. We also thank Enrico Vroombout and Recep Konuksever for their assistance during the data collection process.

I. Introduction

Institutional investors display a tendency to follow each other's investment decisions. John Maynard Keynes in *The General Theory* (1936, pp. 157-158) suggests that reputation concerns can push investors to act similarly. Uniform investment decisions are also a consequence of similar decision problems or similar information sets (Bikhchandani and Sharma (2001)). A group of institutional investors who trade in the same direction is commonly defined as herd behavior (Nofsinger, J. R., & Sias (1999); Sias (2004)). This behavior is even more likely to occur if institutional investors are interconnected. The increasing pace of globalization, financial integration, and national regulations cause financial institutions such as institutional investors to be more and more interconnected (Chan-Lau (2010)). It is therefore important to consider the impact of interconnectedness on the strategic decision-making of these institutions.

The well-developed sector of occupational pension funds in the Netherlands is an important example of a highly interconnected group of institutional investors. The Netherlands, with a population of 17 million inhabitants, is a small country. Nonetheless, it has one of the largest funded pension sectors in the world. It has broad coverage. More than 91 percent of workers are covered and currently there are 3 million retirees. The total assets under management amounted to 196 percent of the national GDP as of 2016. These figures show the importance of the pension sector in the Dutch economy and justify a high level of regulation. The pension fund sector has undergone a significant consolidation over the last decade. The number of occupational pension funds decreased from 833 in 2007 to 297 at the end of 2016. Also, the number of people with key positions in the sector, such as trustees and consultants, is not large. Moreover, the number of asset managers and actuarial firms working for the pension funds is rather small. As a consequence, board interconnections as well as multiple appointments of asset managers and actuarial firms frequently occur. All these factors together result in a highly interconnected sector. The pension sector in the Netherlands is therefore a close network of interconnected people and institutions.

We use a unique dataset on the governance structures of 191 Dutch pension funds to study the effect that interconnections have on strategic investment decisions. We define interconnections among pension funds as occurring via trustees, actuaries, or dominant asset managers who provide services to multiple pension funds.[1] We focus on the strategic allocations of alternative asset classes, in particular real estate, private equity, hedge funds and commodities. These asset classes are often more complex, less liquid, and riskier than standard asset classes such as equity and fixed income. As such, alternative asset classes require that decision-makers have specific knowledge on them. Moreover, decision-makers often have trouble accessing information about alternative asset classes. Therefore, decision-makers who are the pension fund trustees logically are tempted to gather such information from a group of peers in order to shape their own investment beliefs about these asset classes.

Our contribution to the literature is the following: We investigate the impact of interconnections on pension funds strategic asset allocations (SAA). We focus particularly on alternative asset classes that can be more sensitive to interconnection effects. Interconnections can lead to herd behavior in investment decisions. By relying on spatial econometrics, we develop a novel measure for this behavior. We measure herding as the cross-sectional temporal dependence of the strategic portfolio weights of interconnected pension funds over subsequent periods. Our method provides a framework within which pension funds herd and shows that interconnections are an important driver of similar investment decisions. In contrast to prior studies (Lakonishok et al. (1992); Sias (2004)), we are therefore able to highlight a channel that leads pension funds to herd. Our unique data allows us to clearly identify interconnections in many dimensions within the pension funds governance spectrum. Moreover, the detailed information about the SAAs of pension funds allows us to assess the complete portfolio strategy of pension funds. The SAAs are the main determinant of the pension funds performance (Brinson et al. (1986); Brinson et al. (1991)). Therefore, strategic investment decisions are highly relevant for the long-term sustainability of pension funds.

Pension funds in the Dutch occupational pension system are private, nonprofit financial institutions. A board of trustees is responsible for the administration of the pension scheme on behalf of its stakeholders. This responsibility involves managing the scheme, collecting contributions, investing the pension funds money, and paying out the pensions. Trustees therefore have the formal decision power over the SAA.[2] Every board's decision has to balance the interests of all stakeholders in the pension fund: retirees, employees, and employer(s). The composition of the board of trustees is therefore typically based on stakeholder representation. However, the possibility also exists to have one or more independent trustees on a board. One person can sit on multiple boards of trustees. Such a multiple appointment might lead investment beliefs of the individual trustee to be transferred across pension funds. A trustee could, for example, increase his or her reputation among peers if an investment that was recommended by him or her significantly outperformed the benchmark return. However, we argue that this transmission channel is quite strained for three reasons. First, the different characteristics of each pension fund determine to a large extent the investment policy. Second, an individual trustee is unlikely to have the capacity to influence the decisions of other board members given that investment decisions have to be approved by a majority of the board. The assumption that individual trustees have this power in multiple pension funds is a rather strong assumption. Third, the board is typically supported by an investment committee when it comes to investment decisions. This administrative body typically includes some trustees and some external advisors. The main tasks of the investment committee consist of advising the board of trustees on investment policies, formulating policy proposals for the board, and monitoring the implementation of the investment policy by the asset managers. Even though the board of trustees is formally in charge of making investment decisions, the investment committee typically influences these decisions. This committee is a countervailing power against dominant trustees.

Each pension fund also relies on the services of two actuaries: an advisory actuary and a certifying actuary. The advisory actuary advises on the level of contributions that should be paid to the pension fund for the accrual of new pension benefits. He or she also determines the value of the liabilities. The value of the pension liabilities is calculated as the discounted value of the accrued pension rights. Changes in this value are due to variations in the market interest rate, indexation, and actuarial factors such as demographic trends. The value of pension liabilities is necessary to determine the funding ratio of the pension fund. The advisory actuary can also be involved in the design and execution of the Asset and Liability Management study (ALM) that a pension fund performs. The ALM study assesses the long-term impact of investments, contributions, and benefit policies on the funding ratio and the claims of the various stakeholders (Blome et al. (2007); Bauer et al. (2006)). Given the key role of the SAA in the ALM study, the advisory actuary can influence the board's decisions with his or her investment beliefs. The technical knowledge that he or she possesses makes his or her opinion valuable to trustees in SAAs. In case an advisory actuary advises multiple pension funds, we can expect his or her investment beliefs to affect these pension funds. Moreover, the company the advisory actuary works for might affect a pension fund's investment decisions as well. Actuarial firms build their stochastic ALM models on specified theoretical assumptions (e.g., mean-variance characteristics of asset classes returns). Therefore, pension funds that share advisory actuaries that work for the same company are more likely to display SAAs that reflect the same financial assumptions.

At the contribution level, ALM and the investment policy must be certified by an independent actuary. By law, the certifying actuary must be a person different from the advisory actuary. Given that his or her function is limited to an ex-post assessment of the adequacy of the investment policy, there is no direct channel for a certifying actuary to influence SAAs. However, the certifying actuary can place a remark if he or she believes the investment policy is not in line with the prudent person rule. Therefore, the certifying actuary can also influence a pension fund's strategic investment decision. Furthermore, a certifying actuary can be employed as advisory actuary in other pension funds (vice versa). Therefore, multiple appointments and the possibility to cover both functions allow the same actuary to affect the investment decisions of multiple pension funds. As a consequence, a reasonable hypothesis is that investment beliefs are easily transferred by both types of actuaries.

Pension funds hire asset managers to implement and execute the investment policy approved by the board of trustees. This is also a transmission channel for herd behavior. Asset managers influence the board of trustees by discussing their investment beliefs. Some pension funds even adopt a governance structure in which a fiduciary asset manager is appointed not only to execute but also to advise on the investment policy on behalf of the board of trustees. Thus, a fiduciary asset manager clearly has the ability to advise on an investment policy for a pension fund that is in line with his or her own investment beliefs. Their skills and negotiation power allow fiduciary asset managers to push the investment beliefs of pension funds more in line with theirs. Moreover, if the fiduciary manager is also the executor of the investment strategy, he or she has a clear incentive to select asset classes and external asset managers that deliver efficiency gains. In case of multiple mandates, similar investment strategies can be implemented across pension funds based on the fiduciary asset manager's preferences.

Our key results are as follows: First, over the entire sample period of 2007 through 2016, pension funds interconnected through actuaries and asset managers make similar strategic investment decisions, especially in alternative asset classes. Second, the interconnections among asset managers generates strong herd behavior in all asset classes, except for real estate. Therefore, the influence of asset managers is not only isolated to asset classes where information is scarce and high knowledge is required but also to alternative assets. Third, the interconnection effect of individual actuaries on the total alternative asset portfolio is strong, while herding in individual alternative asset classes occurs in some years only. Fourth, individual actuaries lead to herd behavior among the pension funds they advise, regardless of their function (advisory vs certifying) or the firm they work for. Fifth, there is no compelling evidence that the trustees interconnections lead to herding in the decision to change alternative asset portfolios. An exception is private equity, where herding is recorded in some years. Interconnections facilitate a transfer of information among pension funds. Given the number of trustees, actuaries, and asset managers, it is impossible to have no interconnections among pension funds. Pension fund networks, originated by multiple appointments of trustees, actuaries and asset managers, are an endemic feature of the Dutch pension system. The analyzation of the effect from pension fund interconnections on strategic investment decisions is nonetheless important for two reasons. First, herding can lead pension funds to develop an alternative asset portfolio that is not in line with their knowledge level. Our work sheds light on the dominant role that actuaries and asset managers play in strategic decision-making, both in terms of advisory power and in terms of information transfer among different pension funds. Furthermore, the effect of actuaries and asset managers on the SAA is stronger than the effect of interconnected trustees. Notwithstanding that the latter retain the formal decisional power, the former have the capability to influence decision-making because of their expertise and persuasiveness. Second, herding can lead pension funds to develop an alternative asset portfolio that is not in line with their liability structure. We show that pension funds with similar liability durations do not have portfolio comovements. We therefore argue that investment decisions affected by interconnections are at least as important as investment decisions based on the liability structure.

The remainder of the paper is organized as follows: In section II, we describe the interconnections that exist among Dutch pension funds and how these can drive herd behavior. In section III, we explain the method that we apply to test our hypothesis. In section IV, we give the details of the data we use to carry out the analysis. In Section V, we describe the results of the study. We provide some robustness checks in section VI, and in section VII we conclude.

II. Interconnections and herd behavior

Pension funds in the Netherlands are highly interconnected that makes this sector an ideal environment to test the impact of interconnections on strategic investment decision-making. Most pension funds in the Netherlands execute defined benefit schemes. Therefore, they have a clear asset-liability perspective.

A. Interconnections and strategic asset allocation

The objective of a pension funds' investment strategy is to choose the optimal risk-return trade-off given the characteristics of the liabilities. A unique optimal SAA for a pension fund does not exist in theory. However, pension funds with similar liability durations can display similar SAAs. Yet we show that the SAAs of pension funds with similar liability durations are quite different and tend to move independently from each other over time. By the same token, pension funds that have different liability durations should have different SAAs. Instead we observe a similar average SAA across pension funds grouped by liability duration. Figure 1 displays the average SAA of pension funds that are grouped by maturity. We observe on average similar portfolios if we compare Panels (a) through (d). This is striking because the difference in average duration between two consecutive groups is approximately two years, which is a considerable difference. The similarities are even more pronounced if we focus on the alternative asset classes with stable allocations of around 10 - 11 percent across groups. Only the group of young pension funds allocates less to alternatives. Figure 2 shows the average allocation to alternative asset classes. Again, the differences between the panels are small. All groups allocate the largest share to real estate. Each allocation to private equity, hedge funds, and commodities is at around 1 percent. Only the group of oldest pension funds allocate 2 percent to hedge funds.[3]

On the one hand, when grouping pension funds by their liability duration, we observe similar average SAAs across different groups. On the other hand, Dutch pension funds seem to invest independently with respect to other pension funds of similar liability duration. This independence casts some doubt on the use of liability duration as a key input parameter for strategic decision-making. The question that naturally arises is whether other factors such as interconnections could explain such dissimilarities within and similarities across groups of pension funds.

We hypothesize that interconnections cause pension funds to make similar investment decisions. This effect should be stronger in alternative asset classes as these require more knowledge. If similar investment decisions are not a consequence of a similar liability duration or pension funds' other similar characteristics, it follows that connected pension funds may display herding.

Our study extends the herd behavior literature by providing a framework within which pension funds herd and by showing that interconnections can drive this behavior. In addition, we focus our analysis of herding on the pension funds strategic decision-making, which to the best of our knowledge has not been studied before. Most papers lack information on SAAs and focus on actual portfolio weights. However, SAAs are the single most important determinant of pension funds performance (Brinson et al. (1986); Brinson et al. (1991)). Moreover, our interest concentrates on alternative asset classes that have not received much attention in the prior research, which mainly focuses on equity investments.

We argue that the incentive to herd in alternative asset classes can be particularly strong. Alternative asset classes often have a reduced amount of information available, low liquidity, high volatility, and require specific expertise. These attributes make skilled and experienced asset managers very influential players in the investment decision process.[4] Moreover, knowledge sharing has a beneficial impact on performance in alternative asset classes (Humphery-Jenner (2013)) and can help pension funds' trustees in forming investment beliefs. Thus, investment decisions that concern alternative asset classes can be sensitive to the decisions made by interconnected pension funds. In line with this sensitivity, we should see strategic investment decisions in alternative asset classes that are less driven by the pension funds' characteristics than by the group of their interconnected decisions (Binfare et al. (2018)).

Both stocks and bonds are liquidly traded in well-developed and efficient markets. Moreover, stocks and bonds have always been in the portfolio of pension funds. Thus, a reasonable assumption is that trustees can develop sufficient knowhow to form independent opinions about these two asset classes. Although we do not rule out the possibility that Dutch pension funds herd in equity and fixed income markets, we believe that factors other than the interconnections mainly drive this herding, such as reputations, regulations, or asset characteristics. Bikker and Koetsier (2017) provide evidence of pension funds' herding in fixed income investments. The authors identify the macroeconomic and financial market environment as well as institutional factors such as regulation and government effectiveness as the main drivers of herding.

In summary, alternative asset classes are the natural investment type in which we can expect a more pronounced interconnection effect on investment decisions, which translates into herd behavior. In line with this expectation, we test whether pension fund's interconnections influence the decision to change the SAA to alternative asset classes over time. Interconnected pension funds should over time show a positive correlation among their strategic portfolio shares in alternative asset classes.

B. Herd behavior in the literature

Herding among financial institutions occurs when a group of investors follow each other into (or out of) the same securities or asset classes over some period of time (Sias (2004)). Paying heed to what everyone else is doing can be rational because the decisions of others might reflect information the decision-maker does not have access to. Moreover, Scharfstein and Stein (1990) shows that although herding can be inefficient from a social perspective (Banerjee, A (1992)), it can be rational when the decision-makers are concerned about their reputation. This concern is applicable to corporate investments, decision-making within firms, and in the stock market. Lakonishok et al. (1992) provide a well-known measure of herding among institutional investors by testing for the cross-sectional temporal dependence of trades. The authors posit that institutions are primarily buyers (sellers) of a security in a period, if they follow each other into (out of) the same security over time. Sias (2004) measures herding by estimating the cross-sectional correlation between mutual funds demand for a security over subsequent quarters. Blake et al. (2017) use the same method to show herding among British pension funds and find that they behave as contrarian investors by means of their portfolio re-balancing strategies. Re-balancing indicates that pension funds' herding does not destabilize financial markets.

More generally, institutional investors' herding can be divided into five subcategories: informational cascades, investigative herding, reputational herding, fads, and characteristic herding (Nofsinger, J. R., & Sias (1999); Graham (1999); Wermers (1999) discuss in detail all these classifications). In this paper, we show an example of characteristic herding, namely institutional investors herding to (out of) an asset class because they are attracted by some characteristic of this asset class. Moreover, our results also relate with investigative herding, which refers to investors that base their investment decisions on the same set of information. Broeders et al. (2016) also study herd behavior among Dutch pension funds and distinguishes between weak, semi-strong, and strong herding. In their findings weak and semi-strong herding are consistent with investigative and characteristic herding, and strong herding is an example of reputational herding.

By testing the effect of interconnections on herd behavior, we also build on the social network literature. Social networks are structures composed of nodes of people or institutions that are interconnected through various social relationships that range from casual to close bonds.[5] Cohen et al. (2008) find that managers of mutual fund portfolios place larger and more concentrated investments in companies to which they are interconnected through an education network. This is a clear example of how interconnections can affect investment decisions, since these portfolio managers perform significantly better with interconnected positions than with non-interconnected positions. Our work closely relates to Bouwman (2011), who focuses on the propagation of governance practices across firms that share directors. This author states that, "*shared directors create a social network of firms, and the governance practices of firms within the network are then influenced by each other in a manner akin to the way other social networks affect patterns of their members.*" Thus, we identify a social network of pension funds via their interconnections and then test for the propagation of investment decisions. The networks of pension funds result from the interconnections among trustees, actuaries, or asset managers who work for multiple pension funds[6] in line with the sociology literature that considers the linkages among corporate board members as a measure of a personal network. See, for example, Mizruchi (1982); Useem (1986).

III. Methodological considerations

Herding is typically measured as the cross-sectional temporal dependence on the net demand of investors for an asset within the same period (Lakonishok et al. (1992)), or over subsequent periods (Sias (2004)). Our data allows us to observe the SAA of Dutch pension funds that is a direct reflection of their investment decisions. The SAA is not affected by market fluctuations. Therefore, it can be used to determine whether pension funds invest similarly over time. We develop a novel measure of herding that tests for cross-sectional temporal dependence among strategic portfolio weights over time. Furthermore, by relying on spatial econometrics we can assess the herding of interconnected pension funds.

Spatial econometrics measure the spatial dependence that arises when the values of a variable observed in one location depend on the values of the same variable observed in nearby locations (LeSage and Pace (2009)). More formally, spatial econometrics deals with the cross-sectional correlation between the observable or the unobservable (error) component of a model. If the correlation arises due to spatial dependence, then the model shows that the dependent variable is a function of observations in neighboring regions. In this case, spatial econometrics estimate the model parameters of an equation that includes variables belonging to other regions (Anselin (1988)).

Relying on this method, we extend the definition of neighboring regions to neighboring pension funds, which we call "interconnected" pension funds. The proximity is not given by geographical distance but rather by decisional power. The proximity of decisional power is the overlaps among trustees, actuaries, or asset managers that work at multiple pension funds. Hence, we argue that in our data generating process (DGP), the values observed at one pension fund depend on the values observed at the interconnected pension funds. We are not the first to use spatial econometrics outside the framework of geography. The literature finds that "space is more than geography" and covers numerous examples (Beck et al. (2006); Dow et al. (1984); Simmons and Elkins (2004)).

To study the herd behavior of connected pension funds, we first interconnect pension funds through overlapping trustees, actuaries, or asset managers. Second, we measure the behavior by assessing the spatial correlations among the SAAs of interconnected pension funds. Therefore, our novel measure of herding captures the impact of interconnections on SAAs and allows us to identify a channel that leads pension funds to herd. Below we give the details of the method we use to measure the herd behavior of pension funds.

A. Spatial autoregressive regression model and weighting matrix

The spatial autoregressive model is a linear regression model in which the assumption on the cross-sectional independence of observations is relaxed. If we take two interconnected pension funds i and j, where y_i depends on y_j (and the other way around), then we can define the spatial autoregressive process as

$$y_i = \rho \sum_{j=1}^{n} W_{ij} y_j + \epsilon_i \tag{1}$$

where $\sum_{j=1}^{n} W_{ij} y_j$ is the spatial lag that represents the linear combination of the values of variable y observed in interconnected pension funds. The linear combination is defined by the $n \times n$ spatial weight matrix W. Each element w_{ij} in the weighting matrix W equal one when pension fund i and pension fund j are interconnected and zero otherwise. The weighting matrix is row standardized throughout the entire analysis. This standardization means that the elements of each row of W are adjusted to sum up to unity. Standardizing over rows means that each individual interconnected observation has a weight that is proportional to one over the total number of interconnected observations. Before we continue we need to address two possible issues with our weighting matrix: network dynamics and endogeneity.

The first issue is network dynamics. In the context of geographical proximity, borders are rather stable over time (Mukherjee and Singer (2008); LeSage et al. (2011)). Differently the interconnections among pension funds in our sample period vary every year. Trustees, actuaries, and asset managers can be hired and fired. Therefore, over our 10-year sample period we have ten different weighting matrices for each network. However, the dynamics are less frequent in practice. Board members on average have a tenure of almost eight years, while actuaries' average contract length is nearly five years, and the average tenure of an asset manager is almost six years.[7] In addition, SAAs are revised every three to five years, and it takes time for a pension fund to implement these changes. Once a SAA is decided, the next period portfolio should immediately reflect such a change, but this is rarely the case. Consider for example a large pension fund, a change in the SAA might signal the market and therefore affect prices. For this reason, large pension funds tend to only gradually adjust their portfolios. Furthermore, decisions such as investing or divesting in alternative asset classes take time to implemented. Given lock-up periods and a lack of liquidity, it is not unusual to see the actual investment decisions being fully implemented months or in some cases even years after the board approves them.

After these considerations, we split our 10-year sample in two. We consider the impact of the connections that exist in a given year on the subsequent five years. The underlying assumption is that the decisions taken at a given point in time will see their effects being implemented throughout the subsequent five years. Therefore, we keep the weighting matrix constant for five years.

The second issue is endogeneity. Our aim is to use the interconnections as an explanatory variable of the investment decisions, where the interconnections are given. However, an investment intention can cause the interconnection. The following example explains this intention. Suppose pension fund A is advised to invest in alternative asset class z. Because the pension fund's trustees are not particularity knowledgeable on this asset class, they hire independent trustee y. This trustee already works for pension fund B and it is well known that he or she has excellent expertise in z. This expertise would generate reverse causality in our model. We avoid this issue by excluding the independent trustees from the sample. These are normally hired because of their expertise. We therefore consider only the interconnections identified by the representatives of employer, employees, and retirees. These are typically hired based on representation criteria rather than based on their specific investment expertise.

The same exclusion criteria cannot be applied to asset management firms. Asset managers are hired because of their investment expertise and the problem of reverse causality can be even stronger. We address endogeneity by restricting the analysis to the network of "dominant" asset managers. The asset management firm identifies this type of manager as being employed by a pension fund throughout the entire sample period and managing a relevant share of the pension fund's portfolio. There is only one dominant asset manager per pension fund and since this firm is employed for a long time, we assume that it would have a significant impact on the investment policy of the pension fund. From 2016 onwards, pension funds only report the names of the asset managers that manage more than 30 percent of the assets under management. Assuming a dominant position for these firms in 2016 seems therefore appropriate. In addition, we assume "dominant" managers in 2016 to be "dominant" in the previous years as well, if the pension fund has continuously employed them throughout the sample period.

The interconnections based on the dominant asset managers are therefore by construction constant over time and consequently no new hired managers should be observed. Nevertheless, the funds could have just hired some of the dominant asset managers at the beginning of our sample period as a reflection of pre-sample investment intentions. In this case the argument against network exogeneity is still valid. To be more conservative we then test the interconnection effect of dominant asset managers only on the subperiod of 2012 - 2016. By doing so we are confident in saying that the interconnections are exogenous to any prior investment intentions.

Conversely, no endogeneity problem for the actuary interconnections arises, given that pension funds hire actuary firms without directly knowing the actuary who will work on the ALM studies. In addition, the investment beliefs of an actuary are the same regardless of the company he or she works for. For this reason, we analyze the interconnections based on individual actuaries rather than at the company level.

B. *Connection effect on the investment decisions, a spatial panel approach*

We measure herding by looking at the cross-sectional temporal dependence among strategic portfolio weights of interconnected pension funds. Therefore, we test the existence of portfolio comovements among interconnected pension funds. This is done by estimating the following spatial autoregressive model:

$$\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t \tag{2}$$

This equation is a panel spatial autoregressive regression (SAR) model where $t = 1, ..., T$ identifies the time dimension. $\mathbf{y}_t$ is the portfolio share invested in a given asset class at time t by each pension fund. $\mathbf{X}_t$ is a matrix that contains the characteristics of a group of pension funds such as funding ratio, liability duration, size, and type of pension fund that explain the pension funds SAA. $\boldsymbol{\mu}$ represents the unobserved individual heterogeneity, which we allow to be correlated to the regressors included in $\mathbf{X}_t$ ($Cov(\mu_i, \mathbf{x}_{ij}) \neq 0$). This correlation means that the SAR model is estimated by controlling for the unobserved individual characteristics of each pension fund. This is known as the within effect. Time fixed effects $\boldsymbol{\theta}_t$ are also included to control for the economic conditions that might affect the SAA in a given year. Further, $\boldsymbol{\epsilon}_t$ is the error term such that $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ and $E(\epsilon_{it}\epsilon_{js}) = 0$ for $i \neq j$ and $t \neq s$. The model is estimated by applying the Quasi-Maximum Likelihood (QML) estimation (Belotti et al. (2017))[8].

The spatial correlation coefficient ρ measures the direction and the intensity of herding among interconnected pension funds. A positive and significant ρ indicates a positive spatial correlation among the portfolio weights of interconnected pension funds. This correlation means that the strategic portfolio weights of the interconnected pension funds increase or decrease together over time. In other words, the interconnected pension funds change their SAAs in the same direction.

IV. Data and descriptive statistics

A. *Data description*

To test the effect of interconnections on investment decisions, we use a balanced panel of 191 Dutch pension funds over the period from 2007 - 2016. The data are proprietary and provided by the prudential supervisor of pension funds, De Nederlandsche Bank (DNB). The method we use requires a balanced panel structure of the data. Consequently, pension funds that were liquidated during the sample period are excluded from the analysis. A pension fund in liquidation gradually transfers assets and liabilities to either another pension fund or to an insurance company. Increasing cost effectiveness is the primary reason for liquidations. The gradual transfer of assets can result in a non-representative SAA for these pension funds in the sample. Yet, considering a sample of surviving pension funds could provide a non-representative description of the investment behavior of the actual population of pension funds during the sample period. However, most of the pension funds that liquidated during the sample period were economically non-significant given their small size. Indeed, every year the total assets under management of the pension funds in our sample ranges from 89 percent to 94 percent of the total assets under management of pension funds reporting to DNB. Thus, our sample is a fair representation of the occupational pension sector in the Netherlands. Moreover, the data are free from reporting biases as all pension funds are obliged to report quarterly statements to DNB. Financial information is therefore available on a quarterly basis. Annual information is available on trustees, actuaries, and asset managers that work for pension funds.

Information in these reports on the board of trustees allows us to infer the name, gender, age, tenure, and function of each individual trustee. Furthermore, we know the stakeholder group a trustee represents. A trustee can represent the employer, the employees, or the retirees and former active participants in the plan, who are also called sleepers or dormant members. Moreover, a trustee can be appointed because of his or her particular expertise without representing a specific stakeholder. This figure is called an independent trustee. In addition, every pension fund relies on an actuary firm for advisory purposes. Each year pension funds report to DNB the name of the actuary firm as well as the name of the advisory actuary. Furthermore, pension funds are required by law to have a certifying actuary. Pension funds also report to DNB the names and the firm of the certifying actuary. Further, pension funds report the names of the asset management firms managing their investments to DNB. Before 2016, pension funds reported the names of all asset managers. From 2016 onwards, pension funds are required to communicate only the names of asset managers managing more than 30 percent of total assets under management. However, the supervisory report does not mentioned whether an asset manager is appointed with fiduciary or execution only functions.

Quarterly financial information includes the funding ratio and liability duration. For supervisory purposes, pension funds also report the strategic and the actual asset allocation. For the purpose of our study, we investigate the SAAs. We group the investments into eight asset classes, namely equity, fixed income, real estate, private equity, hedge funds, commodities, cash, and a residual class named other investments, which among others include infrastructure investments. On average pension funds tend to evaluate the SAA every three to five years. For this reason, we aggregate quarterly information into yearly observations. Moreover, there are no quantitative investment restrictions for Dutch pension funds as long as the investment strategy is conducted according to the prudent person principle (Gollier (2000)). A higher risk exposure is translated into a higher risk profile, which translates into a higher required funding ratio for a pension fund.

B. Pension funds interconnections

The interconnections through trustees, actuaries, and asset managers generate networks of pension funds. Table I displays the evolution of the trustees interconnections over time. We record an increasing number of trustees with multiple appointments over time and as a consequence an increasing number of interconnected pension funds. In 2007, 52 out of 191 pension funds were interconnected through 32 overlapping trustees. As of 2016, 95 out of 191 pension funds were interconnected by means of 90 trustees. In the period from 2007 - 2011, the number of trustees was lower than the period from 2012 - 2016. This is due to the different reporting system used in the first half of the sample period. For this reason, we are only able to retrieve the names of trustees over the period from 2007 - 2011 that were still working in 2012. This sample could create a survivorship bias if the trustees that were still employed in 2012 were also particularly influential board members. They could have exploited their strong position to stay in office longer to affect investment decisions. If this is true, then we might overestimate the effect of trustees interconnections in the first sample because we potentially include only influential trustees. However, this bias is not definite. Furthermore, a reliance on a reduced number of trustees means that there are less potential interconnections to observe. Therefore, if any missing observation can affect our results, it would most likely be the reduced number of visible interconnections.

The interconnections that run through individual actuaries are illustrated in Table II. The number of actuaries that advise more than one pension fund steadily decreases over the sample period. In 2007, 75 actuaries interconnected 178 pension funds. As of 2016, 57 actuaries interconnected 187 pension funds. So, the number of pension funds interconnected by means of one of the two actuaries stayed rather constant over time. Further, nearly all pension funds in the sample are interconnected via one of the two actuaries. Table III shows the interconnections that run through asset managers. In 2007, 46 asset managers interconnected 166 pension funds. As of 2016, 158 pension funds were interconnected via 27 asset managers. Over the sample period the number of asset managers working for multiple funds reduces, yet these asset managers are able to interconnect a sizable share of the pension funds in the sample.

In Figure 3, we illustrate the networks of pension funds as of 2012. Each dot is a pension fund. In Panel (a) we see that many pension funds are not interconnected through trustees. In the bottom left corner is a group of interconnected pension funds sharing at least one trustee. On average a pension fund is interconnected to another three pension funds in 2012. The group of interconnected pension funds grows in size over the sample period, as can be seen in Table I. In Panel (b), we see the interconnections that nearly all pension funds are interconnected via one of the two actuaries. On average a pension fund is interconnected to another nine pension funds in 2012. In Panel (c) we see the network of pension funds sharing the same dominant asset manager is by construction constant over time. A pension fund is on average interconnected to another seven pension funds.

C. Strategic asset allocation of Dutch pension funds

Panel A of Table IV contains the summary statistics for the SAAs of the 191 pension funds in our sample. On average, 58 percent of the pension funds' portfolio is invested in fixed income, while 31 percent is in equity. On average, pension funds invest nearly 10 percent of their portfolio in alternative asset classes. Most of which is allocated to real estate (6.7 percent), the remaining part is equally divided among private equity, hedge funds, and commodities (1.2 percent each). However, if we only consider the pension funds that actually invest in alternative asset classes, then their average share is almost 12 percent over the 10-year period, including 8.5 percent in real estate, 2.8 percent in private equity, 4.4 percent in hedge funds, and 3.4 percent in commodities.

The pension funds in the sample have on average a funding ratio of 113.6 percent and are relatively heterogeneous in terms of maturity. The oldest quartile have a liability duration lower than 15.6 years, while the pension funds included in the youngest quartile have a liability duration above 20.1 years. The sample is dominated by a few large pension funds. The two largest pension funds count for 49 percent of the total assets under management in the sample.

There is some time variation in the SAAs to alternative asset classes. Panel (a) of Figure 4 shows that the average SAA dropped between 2012 and 2016 by almost 4 percentage points. Panel (b) shows a similar trend in the real estate portfolio. Commodities and private equity, after recording steady growth over the period from 2007 - 2014, also suffer a general reduction in the last two years of the sample. On the other hand, the average allocation to hedge funds is quite stable over time. However, many pension funds stopped investing in hedge funds recently (Preqin; Jackwerth and Slavutskaya (2016)). Thus, we observe that large pension funds, in terms of portfolio share, reduced their exposure and small pension funds increased their share over the period from 2013 - 2016.[9] These trends can be seen in Panel (e) Figure 4.

D. Governance of Dutch pension funds

Panel B of Table IV contains the summary statistics for the governance of the pension funds in our sample. The mean board size is 7.1 members. The average age of a trustee is 54.5 years, and 25 percent of the trustees are younger than 48. The average tenure of a trustee is 7.7 years. For 25 percent of the trustees, tenure exceeds 10 years. Only 12 percent of the trustees are female. In terms of representation, employers are 45 percent, employees 39 percent, and retirees are 11 percent. Only 4 percent of the trustees are independent.

Actuaries have an average contract length of five years. Roughly half of the actuaries perform advisory services and an equal percentage perform certifying services. An average pension fund employs 3.9 asset managers with an average contract length of 5.7 years. If we exclude the dominant asset manager, then the average contract length is eight years.

E. Herd behavior within maturity groups

In this subsection, we first analyze the SAAs among pension funds of similar maturity. As discussed in Section II, pension funds with similar liability durations should make similar investment decisions. Yet we observe that the SAA of pension funds with similar liability durations are quite different and tend to move independently from each other over time. We show this independence in Equation (2) where each element in the weighting matrix $\mathbf{W}$ equals one if two pension funds belong to the same maturity group and zero otherwise.[10] If we find a positive and significant ρ coefficient, then those pension funds' portfolios move in the same direction within the same maturity group. However, Table V shows that this movement is not the case for any asset class. There is either no comovement or there is negative comovement, for example, commodities and private equity portfolios tend to move in opposite directions within groups. Thus, pension funds of similar maturity do not display a SAA that moves in the same direction over time.

V. Results

A. Interconnection effect on investment decisions

We argue that interconnections affect the decision to change the SAA to include alternative assets. Panel A of Table VI summarizes the estimation results of the SAR model in Equation (2) where the spatial coefficient ρ is the herding measure. We estimate the model for each asset class and for each network separately. We begin by testing the impact of interconnections that existed in 2007 and in 2012 on the subsequent five years. First, we see that the total allocation to alternative assets of pension funds interconnected through trustees evolve independently over time. We therefore reject the hypothesis that herding exists in the overall allocation to alternative assets for pension funds interconnected through trustees. Second, the aggregate SAA to alternative assets of pension funds interconnected through individual actuaries moves in the same direction. The ρ coefficient is positive and significant in both subperiods. This coefficient indicates that pension funds change their SAAs to alternative assets similarly over time, which is in line with the herd behavior hypothesis. Third, pension funds interconnected through their dominant asset managers also invest similarly in alternative asset classes over time.

When we look at each asset class, there is evidence of herding in commodities and private equity among pension funds interconnected through trustees. However, significant results exist only for interconnections running in 2007. Pension funds sharing an actuary herd in commodities over both periods. Herding also occurs in the second period in private equity and real estate. Furthermore, we observe herding among pension funds interconnected through dominant asset managers in commodities, private equity, and hedge funds. Furthermore, the ρ coefficients are typically larger for pension funds interconnected through dominant asset managers than through actuaries. This coefficient indicates that asset managers have a greater impact on pension fund's investment decisions.

Overall, we conclude that there is an interconnection effect on the decision to change the SAA to alternative asset classes. This effect is particularly strong for dominant asset managers, and it causes herd behavior in all asset classes, except real estate. Numerically, the effect of a ρ coefficient of 0.246 for the aggregate portfolio of alternative assets is as follows: For a pension fund interconnected to two other pension funds in a given year, if both the interconnected pension funds increase their exposure to alternatives by 10 percent, then the first pension fund will increase its allocation of alternatives by 2.5 percent, all else being equal. For more details on the calculation of this effect we refer to Appendix A.

Individual actuaries interconnections also lead pension funds to herd in the aggregate portfolio of alternative investments, while herding in individual asset classes is more period specific. There is little to no evidence of an interconnection effect for trustees. This lack of evidence might be consistent with the fact that many trustees do not have a strong financial background. Trustees who also sit on the investment committee might have more financial knowledge and a greater involvement in the investment decision-making. We also test the impact of pension funds interconnected through trustees who are also in the investment committee. The results are unchanged.[11] These results indicate that even trustees with a stronger financial background and multiple appointments are not able to influence strategic investment decisions in different pension funds.

We focus the study of the herd behavior on alternative investments because the particular characteristics of this asset class are expected to accentuate it. By the same token, we should observe a lower or non-existent effect from interconnections in equity and fixed income, given the more standardized features of these securities. In Panel B of Table VI, we indeed observe very little evidence of portfolio comovements among pension funds interconnected through trustees and individual actuaries. The fixed income portfolio of pension funds interconnected through individual actuaries move in the same direction but only for interconnections in 2007. In addition, the degree of spatial autocorrelation is lower than in any other alternative asset class, which confirms the hypothesis that the network effect, if present, is stronger in alternative investments. Conversely, the interconnection effect for dominant asset managers is also strong on the decision to change the strategic allocation to equity and to fixed income. The ρ coefficient is comparable in magnitude to the ones found for alternative investments in Panel A. This coefficient means that dominant asset managers are able to influence most of the strategic investment decisions in their network of interconnected pension funds.

B. *Herd behavior over time*

We have found evidence of herding in interconnected pension funds. However, we concentrated our analysis on the network of pension funds in 2007 and 2012 only. In this subsection, we reestimate Equation (2) with all the weighting matrices between 2007 and 2012 to gauge the evolution of the herd behavior over time. The interconnection effect is estimated every year on the subsequent five years. We present the results for pension funds interconnected through trustees and actuaries. Such an approach is not necessary for dominant asset managers interconnections given that the weight matrix is constant over time by construction.

In Figure 5, we show the estimation results of the model for trustees interconnections. We observe weak evidence of herding in the aggregate alternative asset portfolio. The ρ coefficient is positive and significant only when testing the interconnections in 2008 and 2009. Furthermore, pension funds interconnected through trustees do not display any portfolio comovements in their equity and fixed income portfolios. The negative and significant ρ coefficients displayed by the fixed income portfolio illustrate that interconnected pension funds' portfolios move in the opposite direction over time. These findings reject the herd behavior hypothesis. Figure 6 displays the results for each alternative asset class separately. Consistent evidence of herding among interconnected pension funds is only recorded in private equity. Also, positive and significant ρ coefficients are recorded for hedge funds and commodities, but only in some years.

In Figure 7, the model is estimated for pension funds interconnected through individual actuaries. We observe that herding in alternative asset classes is recorded throughout the entire sample period. The ρ coefficient is positive and significant every year except for 2009. Overall the herd behavior has decreased from 2007 until it disappears in 2009. However, from 2010 onward it increases again. This increase shows that the effect of the actuaries interconnections gained in power from 2010 onwards. Conversely no significant comovements are recorded in the equity and fixed income portfolios of interconnected pension funds. These results strengthen the finding in Panel A of Table VI and confirms that interconnection-driven herding should be stronger in alternative asset classes. Figure 8 displays the results for each alternative asset class separately. Panels (a) and (b) show evidence of herding among interconnected pension funds in private equity from 2008 onwards and real estate from 2009 onwards. This herding confirms the results in Panel A of Table VI. Conversely, no herding is recorded in the hedge fund portfolio. Further Panel (d) highlights that herding in commodities is recorded only via actuaries interconnections that existed in 2007 and 2012.

C. Disentangling actuaries interconnection effect

Pension funds interconnected through individual actuaries show herd behavior in their alternative asset portfolios. We find this behavior by interconnecting pension funds when they share at least one of the two types of actuaries. Yet the advisory actuary and the certifying actuary have distinctly separate roles. The advisory actuary can affect a pension fund's investment decisions ex ante through his or her consulting activity and via the ALM study. Conversely, the certifying actuary can affect a pension fund's investment decisions ex post by requesting to modify some of the assumptions included in the ALM or to change the investment policy. In order to disentangle the impact of each type of actuary on the investment decisions, we interconnect pension funds that share either the advisory or the certifying actuary. By doing so, we reduce the amount of interconnections among pension funds. On average, three pension funds are interconnected for both networks.

One might expect the advisory actuaries to be in a better position to directly influence investment decisions because they advise board members already in an early stage of the ALM study. In doing so, they can directly transfer their own investment beliefs to the board members. In addition, they could be tempted to implement only small changes to the same ALM model to different pension funds for cost efficiency. Conversely, certifying actuaries could see their influence limited to the ex post review of the ALM study and investment policy.

We test for herding among for the two types of interconnections separately and we show the results in Figure 9 and Figure 10. We find that pension funds interconnected through the advisory actuary display stronger herd behavior in their alternative asset portfolios than pension funds interconnected through the certifying actuary. The ρ coefficients estimated based on an advisory actuarys interconnections are typically larger in magnitude and more significant than the coefficients estimated based on the certifying actuarys interconnections. This is also true for each alternative asset class.

Furthermore, it is possible that the influence an actuary has on the SAA could be driven by the firm he or she works for, given that actuarial firms base their ALM models on specific theoretical assumptions. However, we find no evidence of herding in the overall strategic allocation to alternatives in pension funds that share the same advisory actuarial firm (Figure 11) and pension funds that share the same certifying actuarial firm (Figure 12). Furthermore, in each alternative asset class, we find no consistent evidence of herding for both pension funds that share the same advisory actuarial firm and certifying actuarial firm.

In unreported results, we observe no herd behavior in equity and fixed income portfolios among interconnected pension funds, which is in line with our previous findings. This lack of herding holds for both pension funds interconnected via one of the two types of actuaries and via the same advisory or certifying actuarial firm.

Overall, we can conclude that pension funds that share the same advisory actuary herd more than pension funds that share the same certifying actuary. However, herding is not driven by the advisory actuary only. Each individual actuary through his or her expertise and experience can influence the SAA. This result arises from the possibility for an individual to be either the advisory or certifying actuary in multiple pension funds at the same time. Actuaries can therefore transfer their own investment beliefs both during the advisory activity and the certifying activity. Therefore, the driver of herding is the individual person rather than a contract that relates the actuary to the pension fund. This reasoning is supported by the larger magnitude of the ρ coefficient shown in Figure 7 and Figure 8 when we disregard the type of actuary as compared to the ρ coefficient recorded for each type of actuary in Figure 9 and Figure 10. Furthermore, pension funds that share the same advisory actuarial firm or the same certifying actuarial firm do not display any herding. This absence indicates that an individual actuary is capable of affecting the pension funds investment decisions regardless of the company he or she works for. Therefore, the investment beliefs that are transmitted from the actuary to the pension funds are his or her own and not the actuarial firms.

D. Implications of herding

Our analysis shows that interconnected pension funds change their SAA to alternative asset investments in the same direction over time, especially for pension funds interconnected through actuaries and dominant asset managers. Information sharing about alternative asset classes does not have to have a negative connotation. Interconnections facilitate the transfer of information and knowledge. However, the fact that we observe no or even a negative correlation among portfolios of pension funds with similar maturities questions the goodness of such an interconnection effect. Actuaries play a role in producing the ALM studies. Therefore, finding portfolio comovements among pension funds interconnected via their actuaries despite differences in liability durations casts some doubt on the adoption of matching liabilities as the main investment criterion of these pension funds. These findings indicate that the actuaries investment beliefs are included in the design of the investment policy next to the matching liability criterion.

Moreover, a strong interconnection effect for actuaries indicates a high capacity of actuaries to influence investment decisions in multiple pension funds, especially in face of a nearly non-existent interconnection effect for trustees. Actuaries are professionals that specialize in the assessment of pension funds' matching assets and liabilities. As a consequence, it is reasonable to believe that actuaries opinions about certain investment strategies could be highly valued, even though actuaries are not in charge of any decision-making. Conversely, the investment beliefs of individual trustees are under the close scrutiny of fellow board members. The board of trustees on average is composed of seven members that discuss and eventually approve the investment strategies with a majority. Hence, the non-significant comovements recorded by pension funds interconnected by their trustees stem from the difficulties of an individual trustee to influence the decisions of the entire board.

The observation of strong comovements among pension funds interconnected through their dominant asset manager is less surprising. Asset managers are hired for the execution of the investment strategies approved by the board of trustees. In principle, they should not influence investment decisions, but in many pension funds they act as a fiduciary asset manager, which indicates they are directly involved in the design of the SAA. As a consequence, the pension funds' investment decisions reflect the managers investment beliefs. Even when asset management firms do not have a fiduciary duty, their skills, reputation and negotiating power are factors that allow them to influence pension funds to adopt investment strategies in line with their own investment beliefs. Since we cannot distinguish between fiduciary and execution only asset managers, we cannot say which of the two mandates affect the SAA more.

Overall, the spatial econometrics approach allows us to find the herd behavior among pension funds that are interconnected through their individual actuaries or dominant asset managers. By using pension-fund fixed effects, we can control for unobserved individual characteristics of pension funds, which include risk aversion. We are therefore confident in saying that portfolio comovements, as described in our work, are the direct consequence of interconnections. Thus, similar investment decisions propagate across interconnected pension funds.

VI. Robustness checks

A. Time dynamics in the SAA decisions

Pension funds that herd could react with a lag to an investment decision made by interconnected pension funds. It could take time before information of interconnected pension funds is transferred and processed. Furthermore, SAAs are typically decided on and implemented gradually over time. There are multiple reasons why. First, it takes time to perform an ALM study and to decide on changes in the SAAs. Second, because of gradual implementation, pension funds limit the potential market impact of significant changes. This is especially true for large pension funds. Third, it may take time to find appropriate investment opportunities. In private equity and hedge funds it is common to go through a due diligence process before committing capital. Fourth, it takes time to find counterparties in divesting less liquid assets. This is typically the case for alternative assets.

As a robustness check, we therefore build a model that captures both of these dimensions. The new model tests whether the investment decisions of a pension fund are affected by the past investment decisions of interconnected pension funds. And we correct for gradual changes in the SAA over time. We do so by estimating the following dynamic spatial autoregressive model:

$$\mathbf{y}_t = \lambda \mathbf{y}_{t-1} + \rho \mathbf{W}\mathbf{y}_t + \gamma \mathbf{W}\mathbf{y}_{t-1} + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t \tag{3}$$

where $\mathbf{y}_t$ refers to the SAAs in an asset class by each pension fund, and $\mathbf{y}_{t-1}$ is the SAAs in the same asset class the year before. $\mathbf{W}\mathbf{y}_t$ is the spatially lagged variable, and $\mathbf{W}\mathbf{y}_{t-1}$ contains the SAAs of interconnected pension funds the year before. $\mathbf{X}_t$ is the usual set of pension funds' characteristics. We estimate the model with pension-fund and time fixed effects. The analysis is carried out in the same fashion as Equation (2). We first take as a reference the interconnections that existed in 2007 and 2012, and we test their impact on SAAs over the subsequent five years. In Table VII we show the results for the three types of interconnections. The aim of such a model is to check whether part of the portfolio comovements, captured by ρ, are also explained by the past investment decisions of interconnected pension funds through γ and through gradual adjustments over time through λ. If ρ is still significant after these two additional variables, then it is a stronger signal of contemporaneous herding.

Focusing on the pension funds interconnected through trustees, we see some evidence of herding in the aggregate alternative asset portfolio for interconnections running in 2007 (Table VII Panel A). However, looking at the results for different interconnections over time in Figure 13, we see that a significant ρ coefficient is only recorded for interconnections in 2007 and 2008. This coefficient confirms that no consistent herding in alternative asset investments is recorded for pension funds interconnected through trustees. Moreover, the γ coefficient is typically non-significant, which indicates that pension funds do not replicate investment decisions taken by interconnected pension funds the previous year. Looking at each individual alternative asset class, we observe results that are in line with the aggregate portfolio. The significant ρ coefficients recorded in Panel A of Table VII are not consistently reported for the subsequent years in Figure13. Also, the γ coefficients tend to be highly non-significant or negative. These findings reject the hypothesis of herding on past investment decisions for pension funds interconnected through trustees in individual alternative asset classes. Further, all asset classes display highly significant λ coefficients. In accordance to what we previously argued, portfolio weights are highly autocorrelated over time. This result confirms that pension funds adjust their strategic portfolios gradually over time. In unreported results, we show that equity and fixed income portfolios display no evidence of herding given that the non-significant ρ and γ coefficients are consistently reported over time.

Focusing on the pension funds interconnected through individual actuaries, we observe some evidence of herding in the aggregate alternative asset portfolio for interconnections running in 2012 (Table VII Panel A). Moreover, a significant ρ coefficient is consistently recorded over time in Figure 14. This coefficient confirms herding in alternative asset investments for pension funds interconnected through individual actuaries. In addition, the γ coefficient is typically either non-significant or negative, which indicates that pension funds do not replicate investment decisions taken by interconnected pension funds the previous year. Looking at each individual alternative asset class separately, we observe herding in private equity and real estate portfolios. Figure 14 shows that positive and significant ρ coefficients are consistently recorded for both asset classes. Also γ coefficients are highly non-significant or negative. All these findings reject the hypothesis of herding on past investment decisions for pension funds interconnected through individual actuaries as well. Further, all asset classes display highly significant λ coefficients. In accordance to what we previously argued, pension funds adjust their strategic portfolios gradually over time. In unreported results, we show that equity and fixed income portfolio display no evidence of herding given that the non-significant ρ and γ coefficients are consistently reported over time.

Focusing on the pension funds interconnected through dominant asset managers, we observe herding in all asset classes except real estate (Table VII). This herding confirms the initial finding of herd behavior in alternative asset classes of interconnected pension funds. Furthermore, pension funds interconnected through dominant asset managers also show herd behavior in their equity and fixed income portfolios, which is in contrast to trustees and individual actuaries interconnections. In unreported results, we show that the γ coefficients are highly non-significant or negative for all asset classes. These findings reject the hypothesis of herding on past investment decisions for pension funds interconnected through dominant asset managers. Further, all asset classes also display highly significant λ coefficients. In accordance to what we previously argued, pension funds adjust their strategic portfolios gradually over time.

Overall, the results of the dynamic spatial autoregressive model in Equation (3) confirm the findings of the static spatial autoregressive model in Equation (2). Pension funds interconnected through trustees do not show significant evidence of herding in the SAA over time. Conversely, herding in alternative asset classes is found for pension funds interconnected through individual actuaries. Pension funds interconnected through a dominant asset manager report herd behavior in all asset classes except real estate. The dynamic model also shows that pension funds do not replicate the past investment decisions of interconnected pension funds. Moreover, there is a strong autocorrelation among portfolio weights in all asset classes. This result confirms that SAAs are implemented gradually over time.

B. Spurious regressions concerns

Since strategic portfolio changes are implemented gradually over time, portfolio weights might display a trend over the 5-year subperiods that we consider for our analysis. Interconnections among pension funds also could display a trend over the same subperiod, given that the number of interconnections increase over time. In order to avoid any possible concern for spurious regressions, we test the following model:

$$\mathbf{\Delta y}_t = \rho \mathbf{W} \mathbf{\Delta y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t \tag{4}$$

where $\mathbf{\Delta y}_t$ includes the change in the portfolio share invested in any asset class between year t and year $t-1$, while all other variables have to be interpreted in the same fashion as in Equation (2). The model is estimated similarly to (2), and ρ still represents the herding measure. With this approach we de-trend $\mathbf{y}_t$ by taking its first difference. This de-trending allows us to avoid any possible concern for spurious regressions.

The results for Equation (4) are reported in Table VIII. No major changes are reported as compared to estimating the model with the dependent variable in levels (Table VI). Pension funds interconnected through trustees show no evidence of herding in any asset class as also Figure 15 shows. Conversely, in Figure 16 we observe significant ρ coefficients for the total alternative asset portfolio as well as the private equity and real estate portfolios. This coefficient confirms the previous findings of herd behavior among pension funds interconnected through individual actuaries. The results for pension funds interconnected through dominant asset managers in Table VIII are unchanged with respect to those in Table VI. This result confirms that pension funds interconnected through dominant asset managers display herd behavior in all asset classes except real estate.

VII. Conclusion

We use a unique dataset on the governance structure and SAAs of 191 Dutch pension funds to study the effect of interconnections on strategic investment decisions. We investigate whether interconnected pension funds change their SAA in the same direction over time, with a particular focus on alternative asset classes. Herd behavior occurs if interconnected pension funds change their SAA systematically in the same direction. We identify the interconnections among pension funds through overlapping trustees, actuaries, and dominant asset managers that provide services to multiple pension funds. We test the interconnection effect with spatial econometrics.

We find a strong interconnection effect in the decision to change SAA to alternative asset classes for pension funds interconnected through individual actuaries and dominant asset managers. This is consistent with the herd behavior hypothesis. Pension funds interconnected through individual actuaries display herd behavior in the overall strategic allocation to alternative asset classes as well as in private equity and real estate allocations. Actuaries are able to affect strategic investment decisions in different pension funds regardless of their function or the actuarial firm they work for. Pension funds interconnected through their dominant asset managers display strong herd behavior in all alternative assets, except real estate. Conversely, an interconnection effect for trustees is isolated to private equity. Pension funds interconnected through actuaries and trustees do not show evidence of herding in their equity and fixed income portfolios. On the contrary, pension funds interconnected through a dominant asset manager display herding in both equity and fixed income portfolios. This finding indicates that dominant asset managers are able to influence investment decisions on most asset classes.

Our results are in line with the literature that shows the existence of herd behavior among pension funds (Broeders et al. (2016); Blake et al. (2017); Bikker and Koetsier (2017)). We show that pension funds herd within a network. Therefore, the existence of interconnections is a necessary condition to observe herding. Different from prior studies (Lakonishok et al. (1992); Sias (2004)), we are able to highlight that interconnections are a channel that leads pension funds to herd. Herd behavior in alternative asset classes is driven by the interconnections that exist among pension funds. By doing so, we provide a possible channel within which pension funds herd. Furthermore, our results shed light on the influence that actuaries and asset managers have on SAA decisions. Even though trustees have decisional power, the actuaries and the asset managers investment beliefs can be translated into the pension funds SAA.

Our findings are coherent with the definition of characteristic herding (Sias (2004)), namely that pension funds invest in alternative investments because they value certain characteristics of these asset classes. Specifically, asset managers and actuaries particularly value or do not value alternative investments and then transfer this belief to the investment policy of pension funds during their consulting. Such herd behavior is also consistent with the definition of investigative herding. Interconnected pension funds react to the same set of information because such information comes from the same source, namely the actuaries or the dominant asset managers. This reaction creates an information spillover across pension funds that precedes the mere observation of the investment decisions adopted by peers. Thus, the herd behavior highlighted in our study is not a simple copying mechanism, but it is rather a shared decision of multiple pension funds that are influenced a priori by the same people and firms.

The implication of herding among Dutch pension funds are twofold. From a micro perspective, we observe pension funds with similar maturities that do not show any portfolio comovements in face of strong portfolio comovements displayed by interconnected pension funds. This finding indicates that network pressure is as important as the matching liabilities criterion in SAA decisions.

Moreover, Dutch pension funds exhibit on average similar SAAs in face of quite dissimilar liabilities structures. By showing that pension funds herd in the same direction, we ague that they could potentially adopt a SAA not appropriate to their organizational structure, knowledge level, and size. From a macro perspective having many pension funds with similar portfolios would expose these pension funds to similar investment risks. These implications are subjects for future research.

Appendix A.

In this appendix we describe how to quantify the herding that occurs among pension funds. Herding is measured by the ρ coefficient in a spatial autoregressive model (SAR):

$$y_{it} = \rho \sum_{j=1}^{n} W_{ij} y_{jt} + \beta \sum_{k=1}^{K} x_{itk} + \theta_t + \mu_i + \epsilon_{it} \tag{A1}$$

where the spatial autocorrelation coefficient ρ is associated with the following endogenous variable $\sum_{j=1}^{n} W_{ij} y_{jt}$ or the spatial lag. $\sum_{j=1}^{n} W_{ij} y_{jt}$ represents the function of the portfolio allocation of interconnected pension funds in a given asset class at time t. Equation (A1) is equivalent to Equation (2). To compute the marginal effect of a change in y_j on the value of y_i at a given time t, we need the partial derivatives of Equation (A1) with respect to y_j

$$\frac{\partial y_{it}}{\partial y_{jt}} = \rho \sum_{j=1}^{n} W_{ij} \tag{A2}$$

All else being equal, the change in the strategic asset allocation of pension fund i (y_i) is a function of the allocation y of interconnected pension funds times ρ. For example, consider three pension funds. Their connections are identified by the row standardized weighting matrix W

$$W = \begin{bmatrix} 0 & 1 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 1 & 0 \end{bmatrix} \tag{A3}$$

This equation means that pension fund 1 and 2 are interconnected. Pension fund 2 is interconnected to pension fund 1 and pension fund 3. Pension fund 3 is interconnected to pension fund 2. Based on Equation (A2) we obtain the matrix of partial derivatives

$$\begin{bmatrix} \frac{\partial y_{1t}}{\partial y_{1t}} & \frac{\partial y_{1t}}{\partial y_{2t}} & \frac{\partial y_{1t}}{\partial y_{3t}} \\ \frac{\partial y_{2t}}{\partial y_{1t}} & \frac{\partial y_{2t}}{\partial y_{2t}} & \frac{\partial y_{2t}}{\partial y_{3t}} \\ \frac{\partial y_{3t}}{\partial y_{1t}} & \frac{\partial y_{3t}}{\partial y_{2t}} & \frac{\partial y_{3t}}{\partial y_{3t}} \end{bmatrix} = \rho \begin{bmatrix} 0 & 1 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 1 & 0 \end{bmatrix} \tag{A4}$$

The results in Table VI show that pension funds interconnected through asset managers display a ρ coefficient of 0.25 for the strategic allocation to alternatives. If we allow the asset allocation of both pension funds 1 and 3 to increase by 10 percent we can compute the effect on the allocation of pension fund 2, all else being equal, as

$$\begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \end{bmatrix} = 0.25 \begin{bmatrix} 0 & 1 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \Delta y_{1t} = 10 \\ \Delta y_{2t} =? \\ \Delta y_{3t} = 10 \end{bmatrix} \tag{A5}$$

Therefore, taking Δy_{1t} and Δy_{3t} as given, Δy_{2t} equals 2.5 percent ($\Delta y_{2t} = 0.25(\frac{10}{2} + \frac{10}{2})$). Namely pension fund 2, interconnected to pension fund 1 and pension fund 3, will increase its allocation to alternative asset class by 2.5 percent in response to an increase of 10 percent in interconnected pension funds, all else being equal.

By contrast, the effects of the independent variables $\beta \sum_{k=1}^{K} x_{itk}$ on y_{it} are not only represented by the partial derivatives. Beta coefficients are only part of these derivatives and the spatial coefficient enters into the calculation. The ρ captures an additional spillover effect via feedback from the spatial lag. For more details on the coefficient interpretation we refer to Chapter 2 of LeSage and Pace (2009).

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Notes

[1] Interconnections create networks of pension funds. We use linkages among nodes (pension funds) to identify two pension funds as interconnected. We do not assess the role of pension funds within their networks. Nor do we make any inference about the closeness or centrality of pension funds in the network (Borgatti (2005); Hanneman and Riddle (2005)).

[2]A detailed explanation of the role of trustees is provided by "*Code of conduct of the Dutch pension funds*":
https://www.pensioenfederatie.nl/stream/codeofthedutchpensionfundsenglish2017.pdf

[3] Focusing on the alternative investment portfolio of pension funds, pension funds with longer liability duration should also be less constrained to invest in illiquid assets. However, as shown in Figure 1, this finding does not seem to be the case. The reason why young pension funds in our sample invest so little in alternative asset classes is due to the two main constraints that pension funds in general face when making this decision. The first is a liquidity constraint, which relates to the pension payments and collateral requirements on interest rate, currency, and other derivatives. The second is a capital constraint, namely pension funds need to hold sufficient capital to manage interest rate risk, market risk, currency risk, and longevity risk. Broeders et al. (2017) conclude that even if young pension funds face lower liquidity constraints their longer liability durations make them more exposed to interest rate risk, which translates into higher capital requirements that constrain these pension funds from increasing their exposure to illiquid assets.

[4] Detailed descriptions of the characteristics of alternative investments can be found in: Jegadeesh et al.; Ljungqvist et al. (2017); Harris et al. (2014); Pagliari (2017); Fung et al. (2008)

[5] The literature on the role of social networks in financial markets has grown significantly in recent years, see Jackson (2006) for a survey of the economics of social networks.

[6]The interconnections stem from the governance structure of pension funds. Therefore, our work also relates to the literature that studies the relation between the governance of pension funds and their investment decisions: Phan and Hegde (2013); Jaiswal (2017); Andonov et al. (2017); Andonov et al. (2018)

[7] Information about the average tenure can be retrieved from Table IV.

[8]This estimation addresses the two complications that arise from the extension of the fixed effect

model with a spatially lagged dependent variable pointed out by Anselin et al. (2008). First, the endogeneity of $\mathbf{W}\mathbf{y}_t$ violates the assumption of the standard regression model that $E(\mathbf{W}\mathbf{y}_t\epsilon_t) = 0$. Second, the spatial dependence among the observations at each point in time can affect the estimation of the fixed effect. See Elhorst (2013) for an excellent overview on spatial panel models.

[9] The statistics produced using the unbalanced panel of all the pension funds reporting to DNB produces figures that are in line with Table IV. No significant differences are recorded in both financial and governance structure information.

[10] Maturity groups are identified in the same fashion as in Figure 1

[11]In an unreported analysis, the results are available on request to the authors.

Table I: **Evolution of trustees connections over time.**
Pension funds indicates the number of pension funds in our sample. Trustees indicates the total number of individual trustees. Multiple trustees indicates the number of trustees sitting on more than one board. Multiple pension funds indicates the number of pension funds with at least one board member that sits on at least one other pension fund's board.

Year	Pension funds	Trustees	Multiple trustees	Multiple pension funds
2007	191	461	32	52
2008	191	595	34	56
2009	191	709	43	58
2010	191	853	51	62
2011	191	1,031	57	72
2012	191	1,284	75	83
2013	191	1,243	78	94
2014	191	1,248	84	91
2015	191	1,226	91	94
2016	191	1,185	90	95

Table II: **Evolution of individual actuaries interconnections over time.**
Pension Funds indicates the number of pension funds in our sample. Actuaries indicates the number of actuaries providing services to at least one of the pension funds in the sample. Multiple actuaries indicates the number of actuaries providing service to more than one pension fund. Multiple pension funds indicates the number of pension funds that rely on the service of actuaries, which are also providing services to other pension funds. The table is based on both advisory and certifying actuaries.

Year	Pension funds	Actuaries	Multiple actuaries	Multiple pension funds
2007	191	110	75	178
2008	191	116	71	184
2009	191	125	73	188
2010	191	122	72	189
2011	191	127	72	189
2012	191	126	69	190
2013	191	123	69	190
2014	191	122	66	187
2015	191	113	66	187
2016	191	98	57	187

Table III: **Evolution of asset managers interconnections over time.**
Pension funds indicates the number of pension funds in our sample. Managers indicates the number of asset managers providing services to at least one of the pension funds in the sample. Multiple managers indicates the number of asset management firms providing service to more than one pension fund. Multiple pension funds indicates the number of pension funds that rely on the service of asset management firms, which are also providing services to other pension funds. (Information about asset managers are only available from 2009 onwards).

Year	Pension funds	Managers	Multiple managers	Multiple pension funds
2009	191	114	46	166
2010	191	107	44	165
2011	191	110	45	168
2012	191	97	46	173
2013	191	92	45	174
2014	191	66	33	162
2015	191	59	31	159
2016	191	46	27	158

Table IV: **Summary statistics.**
Panel (A) reports the quantitative information about the 191 pension funds in the panel. Panel (B) reports the information about trustees and actuaries that are used to identify the interconnections analyzed in this study. The mean (standard deviation) indicates the average (standard deviation) across pension funds and over time for each variable. The asset class allocations are expressed as percentages. For some of the variables, e.g., size, allocations to hedge funds, and private equity, the mean is outside the 25 percent - 75 percent interval. This is due to the skewness in the distribution. All variables are measured across pension funds and over time.

	Obs	Mean	Std. Dev.	25^{th}	75^{th}
A. Pension funds financial information					
Strategic Asset Allocation					
Fixed income	1,910	57.83	15.06	48.18	67.79
Equity	1,910	31.40	10.97	24.48	38.08
Other investments	1,910	0.77	3.89	0.00	0.03
Cash	1,910	0.07	4.03	0.00	0.00
Alternatives	1,910	9.93	8.12	3.90	15.00
Real Estate	1,910	6.67	5.93	1.25	10.00
Private Equity	1,910	1.19	2.63	0.00	0.80
Hedge Funds	1,910	1.19	2.63	0.00	0.75
Commodities	1,910	1.20	2.02	0.00	2.10
Pension Fund Characteristics					
Funding ratio	1,910	113.60	24.67	100.70	117.30
Liability duration	1,910	18.05	3.87	15.6	20.10
Size(000 EUR)	1,910	4,212,385	2.29e+07	181,672	1,458,313
log size	1,910	13.24	1.74	12.11	14.19
B Pension fund governance					
Trustees					
Board size	10,751	7.10	2.63	5.00	9.00
Age (years)	10,751	54.48	9.77	48.00	62.00
Tenure (years)	10,751	7.73	5.11	4.00	10.00
% Female	10,751	12.14	13.87	0.00	20.00
% Employer	10,751	45.27	15.88	40.00	50.00
% Retirees	10,751	11.39	11.69	0.00	20.00
% Employees	10,751	38.92	17.21	30.00	50.00
% External (independent)	10,751	4.05	13.31	0.00	0.00
Actuaries					
Contract length	3,703	5.24	2.56	3.00	7.00
% Female	3,703	13.37	24.51	0.00	0.00
% Advisor	3,703	49.04	6.96	50.00	50.00
% Certifying	3,703	50.96	6.96	50.00	50.00
Asset managers					
Managers per pension fund	2,503	3.89	4.17	1.00	5.00
Contract length	2,503	5.68	2.21	4.00	8.00
Dominant asset managers					
Managers per pension fund	1,064	1.00	0.00	1.00	1.00
Contract length	1,064	8.00	0.00	8.00	8.00

Table V: **Portfolio evolution of pension funds of similar maturities.** The table shows the estimation results for Equation 2, namely the spatial panel autoregressive model $\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$, on the interconnected pension funds for their average liability duration level over time. The dependent variable $\mathbf{y}_t$ contains the SAA to each asset class of each pension fund in year t. ρ is the coefficient that describes spatial correlation among the strategic portfolio weights of interconnected pension funds over time. $\mathbf{W}$ is the spatial weighting matrix of interconnected funds with similar average liability durations over the entire sample period (same maturities groups used in Figure 1). $\mathbf{X}_t$ contains a set of control variables: funding ratio, size, and liability duration of each pension fund. And, $\boldsymbol{\mu}$ and $\boldsymbol{\theta}_t$ indicate pension funds' individual heterogeneity that is fixed over time and the year fixed effects. Positive and significant ρ is the pension funds that belong to the same maturity group that report portfolio weights that move in the same direction over time. We estimate the models for each asset class separately and report the corresponding spatial coefficients.

	Trustees Network						
	Alternatives	Commodities	Private equity	Hedge funds	Real estate	Equity	Fixed income
ρ	-0.166	-0.282**	-0.325**	-0.0889	-0.0174	0.00403	-0.0843
	(-1.09)	(-1.97)	(-2.55)	(-0.48)	(-0.14)	(0.03)	(-0.72)
Duration	-0.166	0.0221	-0.0221	-0.118	-0.0499	0.156	0.331
	(-1.11)	(0.49)	(-0.58)	(-1.31)	(-0.66)	(0.58)	(0.93)
Funding ratio	-0.0261*	-0.00234	-0.00345	-0.00392	-0.0165*	-0.0160	0.0276
	(-1.78)	(-0.58)	(-1.06)	(-0.69)	(-1.70)	(-0.89)	(1.21)
Log size	0.137	-0.0542	0.0135	0.138	0.0519	1.728**	0.874
	(0.41)	(-0.37)	(0.22)	(0.86)	(0.27)	(2.49)	(0.40)
Year FE	YES	YES	YES	YES	YES	YES	YES
Pension fund FE	YES	YES	YES	YES	YES	YES	YES
N	1,910	1,910	1,910	1,910	1,910	1,910	1,910
R^2	0.08	0.02	0.03	0.05	0.02	0.01	0.04

t-values in parentheses. Two-tailed test. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table VI: **Connection effect on the SAA evolution over time.** The table shows the estimation results for the spatial panel autoregressive model $\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$ (Equation 2). The dependent variable $\mathbf{y}_t$ contains the SAA for each asset class of each pension fund in year t. ρ is the coefficient that describes that spatial correlation among the strategic portfolio weights of interconnected pension funds over time. $\mathbf{W}$ is the spatial weighting matrix that identifies the network of trustees, actuaries, or dominant asset managers in year 2007 or 2012 and $\mathbf{X}_t$ contains a set of control variables: funding ratio, size, and liability duration of each pension fund. $\boldsymbol{\mu}$ and $\boldsymbol{\theta}_t$ indicate pension funds' individual heterogeneity that is fixed over time and the year fixed effect. We estimate the model for each asset class separately and report the corresponding spatial coefficients. The coefficients for the control variables are not reported here for brevity.

	Trustees network		*Actuaries network*		*Managers network*
	'07 - '11	'12 - '16	'07 - '11	'12 - '16	'12 - '16
A. *Alternative asset classes*					
ρ Tot. Alternatives	-0.1328	0.088	0.2461***	0.2155***	0.2463***
	(-1.27)	(1.28)	(3.97)	(3.00)	(2.73)
ρ Commodities	0.1882***	-0.0715	0.1650**	0.1379**	0.3599***
	(2.76)	(-0.91)	(2.19)	(2.33)	(4.47)
ρ Private equity	0.1207***	0.0866	-0.078	0.1427*	0.4064***
	(2.73)	(0.79)	(-1.42)	(1.71)	(4.68)
ρ Hedge funds	-0.3158**	-0.0114	0.1347	-0.0761	0.4316***
	(-1.99)	(-0.53)	(1.36)	(-1.12)	(5.17)
ρ Real estate	0.0556	0.0229	0.0770	0.2363***	0.1293
	(1.13)	(0.33)	(1.24)	(2.71)	(1.44)
B. *Standard asset classes*					
ρ Equity	-0.0132	-0.0157	0.1002	-0.0100*	0.3006***
	(-0.22)	(-0.36)	(1.59)	(-1.65)	(4.91)
ρ Fixed income	-0.1068	-0.1087**	0.1149**	0.0821	0.3911***
	(-1.19)	(-2.50)	(2.18)	(1.48)	(4.72)
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Pension fund FE	YES	YES	YES	YES	YES
N	955	955	955	955	955

t-values in parentheses. Two-tailed test.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table VII: **Interconnection effect on the SAA evolution over time - Dynamic specification.** The table shows the estimation results for the dynamic spatial panel autoregressive model $\mathbf{y}_t = \lambda \mathbf{y}_{t-1} + \rho \mathbf{W} \mathbf{y}_t + \gamma \mathbf{W} \mathbf{y}_{t-1} + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$.$\mathbf{W}\mathbf{y}_{t-1}$ contains the strategic portfolio weights of interconnected pension funds the year before. $\mathbf{W}\mathbf{y}_t$ is the spatially lagged variable, and $\mathbf{X}_t$ contains a set of control variables: funding ratio, size, and the liability duration of each pension fund. Also, this model is estimated by using pension fund and year fixed effects. $\mathbf{W}$ is the spatial weighting matrix that identifies the network of trustees, actuaries, or dominant asset managers in year 2007 or 2012. We estimate the model for each asset class separately and report the corresponding spatial coefficients. λ and γ coefficients as well as coefficients for the control variables are not reported here for brevity.

	Trustees network		*Actuaries network*		*Managers network*
	'07 - '11	'12 - '16	'07 - '11	'12 - '16	'12 - '16
A. *Alternative asset classes*					
ρ Tot. Alternatives	0.124**	-0.153**	0.054	0.11*	0.259**
	(2.11)	(-2.09)	(0.74)	(1.88)	(2.50)
ρ Commodities	0.252***	-0.115	0.213**	0.021	0.343***
	(2.64)	(-1.63)	(2.29)	(0.47)	(3.38)
ρ Private equity	0.1445*	0.075	0.06	0.123	0.445***
	(1.92)	(1.54)	(0.95)	(1.43)	(4.64)
ρ Hedge funds	0.036	-0.062**	0.233*	-0.015	0.39***
	(0.25)	(-2.43)	(1.75)	(-0.25)	(5.32)
ρ Real estate	0.132**	-0.179***	-0.141**	0.189**	0.076
	(2.00)	(-3.63)	(-2.26)	(2.36)	(0.97)
B. *Standard asset classes*					
ρ Equity	-0.105	-0.058	0.044	-0.185***	0.299***
	(-1.59)	(-1.51)	(0.59)	(-3.52)	(4.22)
ρ Fixed income	0.105*	-0.17***	0.05	0.044	0.406***
	(1.73)	(-4.69)	(1.18)	(0.69)	(4.83)
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Pension fund FE	YES	YES	YES	YES	YES
N	764	764	764	764	764

t-values in parentheses. Two-tailed test.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table VIII: Interconnection effect on the SAA evolution over time - First difference analysis. The table shows the estimation results for the spatial panel autoregressive model $\mathbf{\Delta y}_t = \rho \mathbf{W} \mathbf{\Delta y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$ (Equation 4). The vector of dependent variables $\mathbf{\Delta y}_t$ contains the changes in the strategic asset allocations to each asset class of each pension fund between year t and year $t-1$. ρ is the coefficient that describes the spatial correlation among the changes in the strategic portfolios of interconnected pension funds over time. $\mathbf{W}$ is the spatial weighting matrix that identifies the network of trustees, actuaries, or dominant asset managers in year 2007 or 2012, and $\mathbf{X}_t$ contains a set of control variables: funding ratio, size, and the liability duration of each pension fund. $\boldsymbol{\mu}$ and $\boldsymbol{\theta}_t$ indicate pension funds' individual heterogeneity that is fixed over time and the year fixed effect. We estimate the model for each asset class separately and report the corresponding spatial coefficients. The coefficients for the control variables are not reported here for brevity.

	Trustees network		*Actuaries network*		*Managers network*
	'07 - '11	'12 - '16	'07 - '11	'12 - '16	'12 - '16
A. *Alternative asset classes*					
ρ Tot. Alternatives	0.0251	-0.0699	0.1919***	0.1084***	0.1784**
	(0.45)	(-1.41)	(2.91)	(2.17)	(2.03)
ρ Commodities	0.2555***	-0.0944	0.1994***	0.0484	0.3419***
	(2.91)	(-1.51)	(2.4)	(1.15)	(3.82)
ρ Private equity	-0.0606	0.0751	0.0618	0.1581**	0.3934***
	(-1.25)	(1.52)	(0.98)	(2.17)	(4.57)
ρ Hedge funds	0.080	0.0441	0.2647***	-0.0597*	0.3733***
	(0.84)	(1.37)	(2.80)	(-1.72)	(4.32)
ρ Real estate	0.0557	-0.0505	-0.0248	0.1738***	0.0087
	(0.96)	(-1.34)	(-0.39)	(3.28)	(0.10)
B. *Standard asset classes*					
ρ Equity	0.0051	-0.0397	0.1401**	-0.1420***	0.2606***
	(0.09)	(-1.06)	(2.38)	(-2.97)	(3.51)
ρ Fixed income	0.0814	-0.1274***	0.1108*	0.0512***	0.3538***
	(1.62)	(-3.54)	(1.93)	(1.01)	(4.07)
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Pension fund FE	YES	YES	YES	YES	YES
N	764	955	764	955	955

t-values in parentheses. Two-tailed test.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

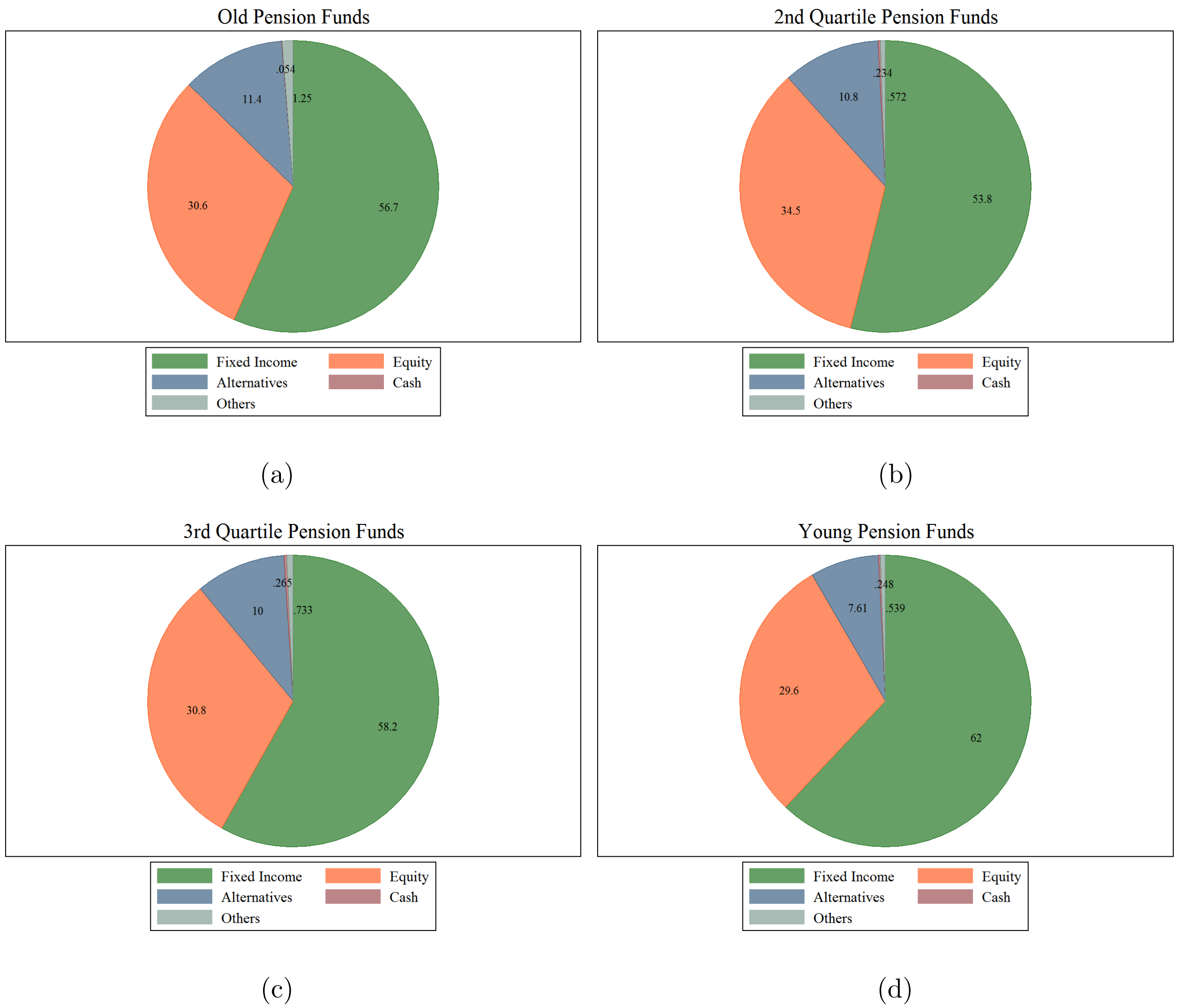


Figure 1. Average strategic asset allocation of pension funds by liability duration groups.
Panel (a) displays the average strategic asset allocation over the sample period of the oldest quartile of pension funds (average liability duration less or equal than 15.88 years). Panels (b) and (c) display the average strategic asset allocation for the second and third quartile of pension funds (average liability duration between 15.88 and 17.42 years and liability duration between 17.42 and 20.01 years). Panel (d) displays the average strategic asset allocation of young pension funds (average liability duration longer than 20.01 years). The four maturity groups are identified by the average liability duration over the entire sample period of each pension fund. The labels have to be read as percentage points over the total portfolio.

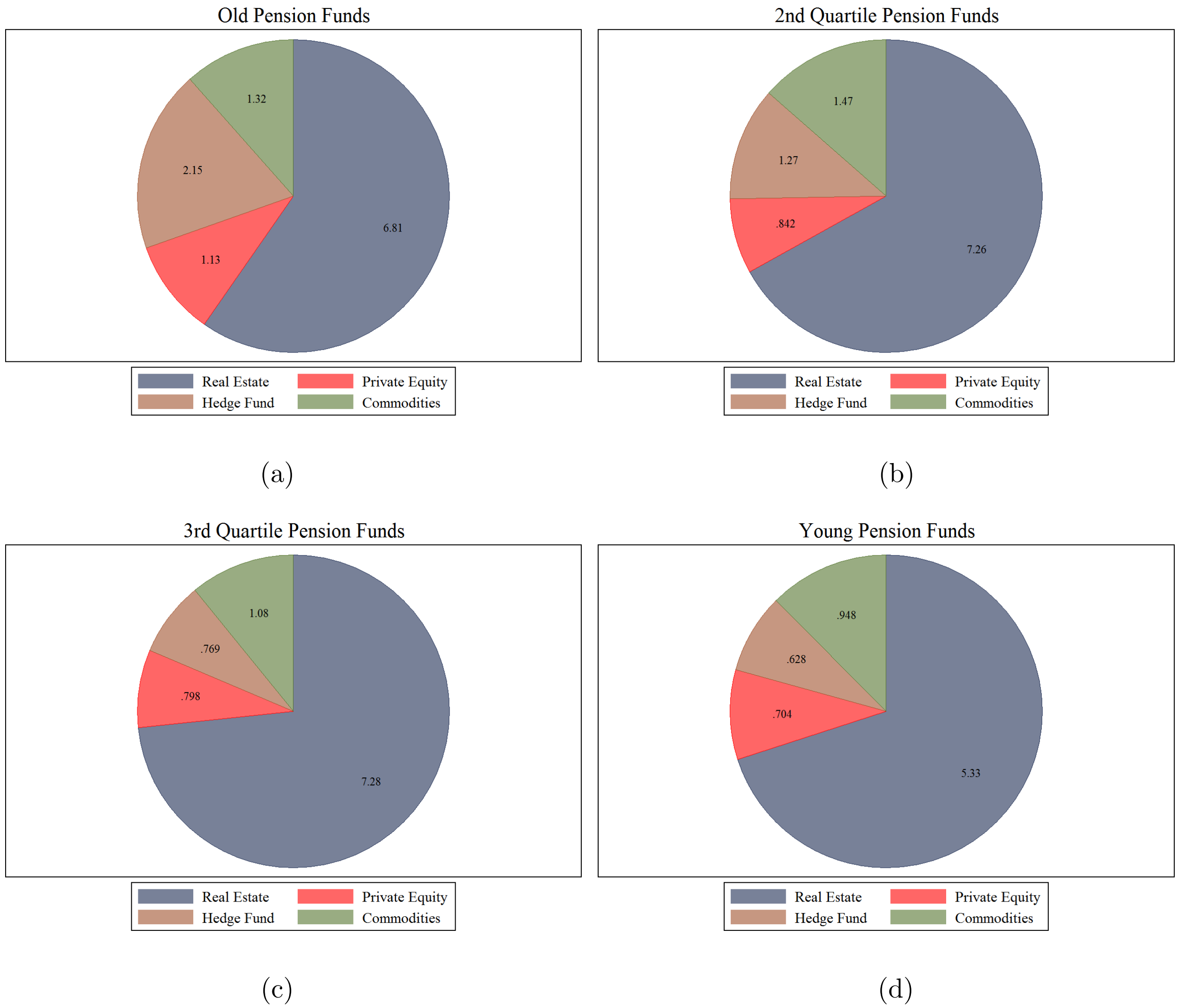
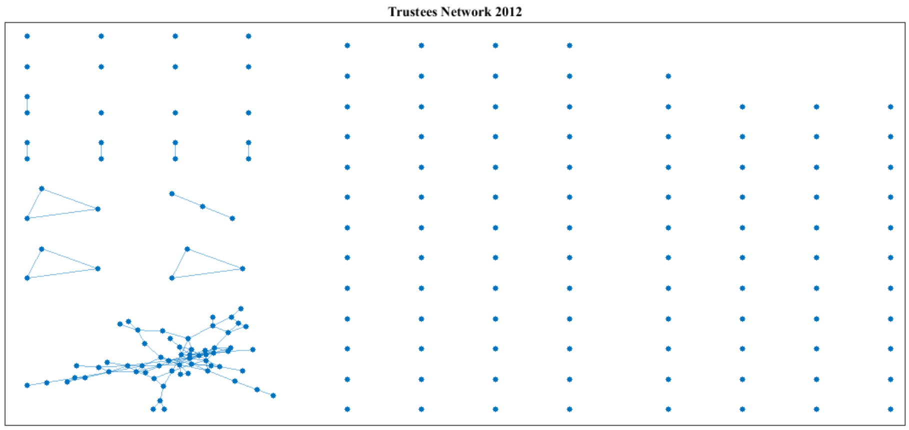
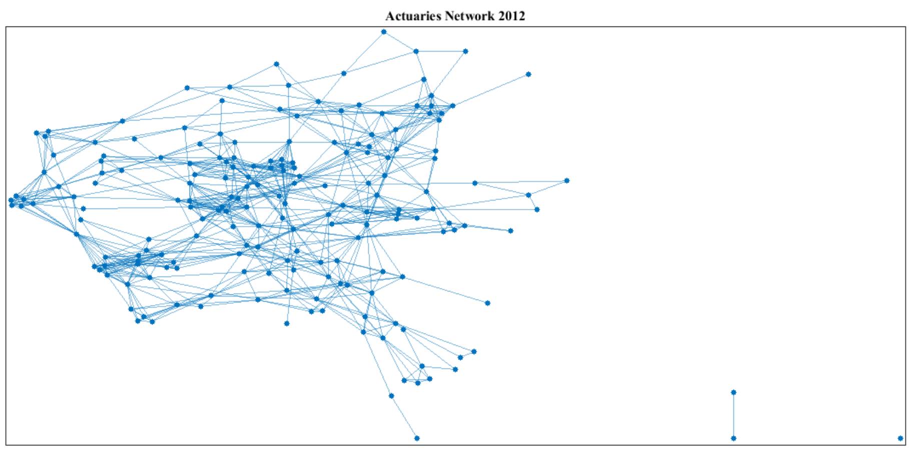


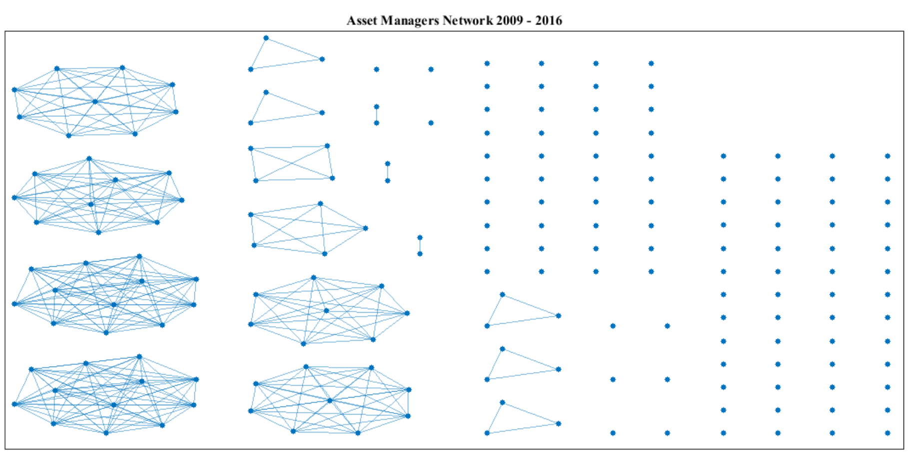
Figure 2. Average alternative portfolios of pension funds by liability duration groups. Panel (a) displays the average alternatives allocation over the sample period of the oldest quartile of pension funds (liability duration less or equal than 15.88 years). Panels (b) and (c) display the average alternatives allocation is displayed for the second and third quartile of pension funds (liability duration between 15.88 and 17.42 years and liability duration between 17.42 and 20.01 years). Panel (d) displays the average alternatives allocation of young pension funds (liability duration longer than 20.01 years). The four maturity groups are identified by the average liability duration over the entire sample period of each fund. The numbers are percentages of the total portfolio, namely the strategic allocation in each alternative asset class.



(a)

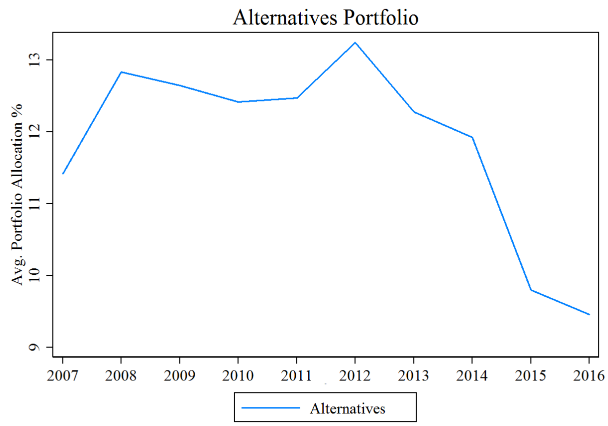


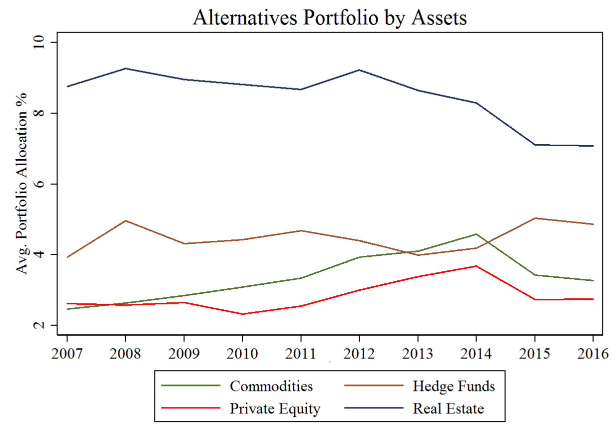
(b)



(c)

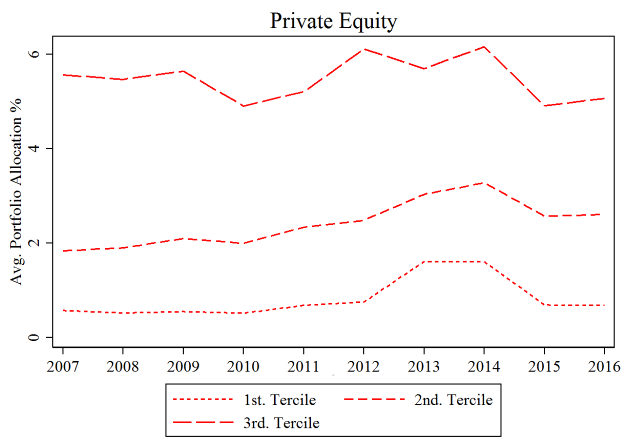
Figure 3. Pension funds networks in 2012.
The figure displays the interconnections running through pension funds. Panel (a) shows the pension funds interconnected that share at least one trustee. Panel (b) shows the pension funds interconnected by one of the two actuaries. Panel (c) shows the pension funds that share the same dominant asset manager.

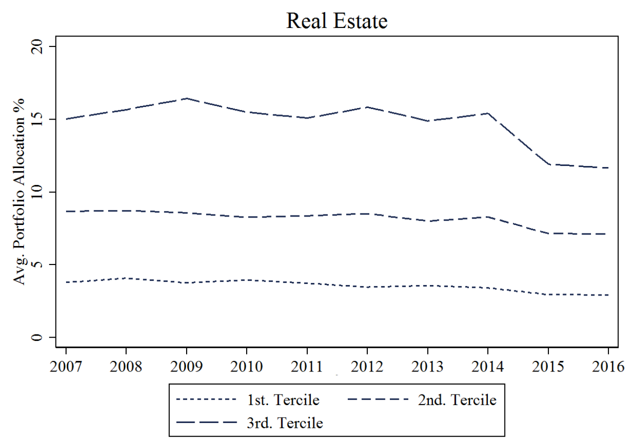




(a)

(b)





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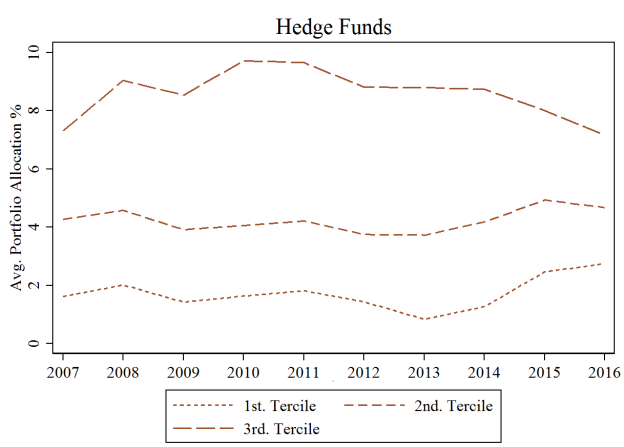
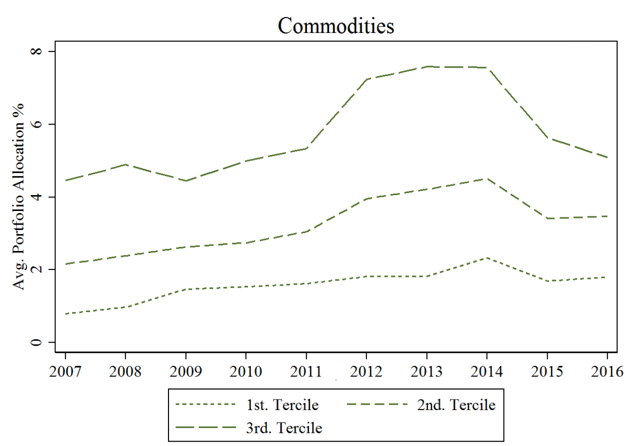
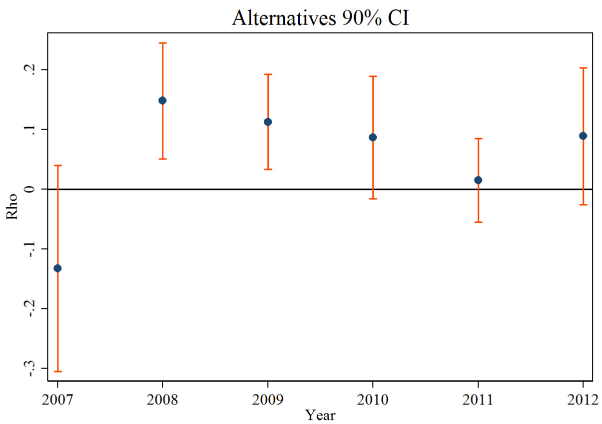




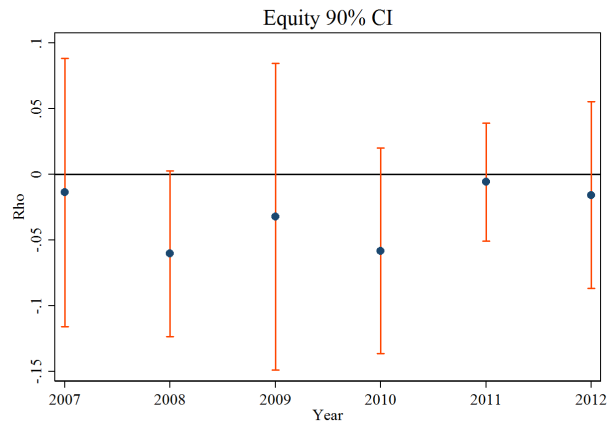
(e)

(f)

Figure 4. Alternative investment portfolio with different investment sizes.
The figure displays the evolution over time of the strategic allocation in (c) private equity, (d) real estate, (e) hedge funds and (f) commodities of the pension funds that invest in these assets. Each panel contains the evolution of the strategic allocation divided by terciles of investment size.



(a)



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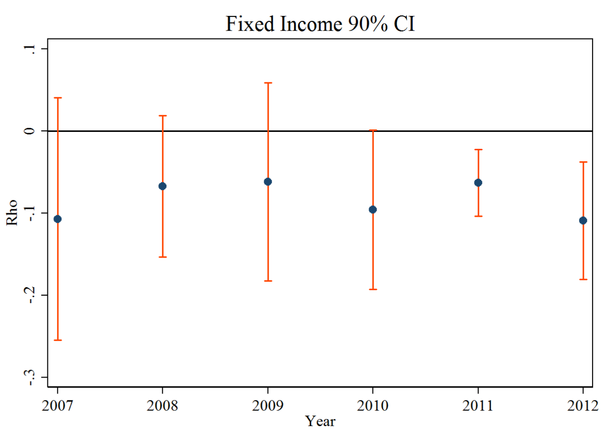
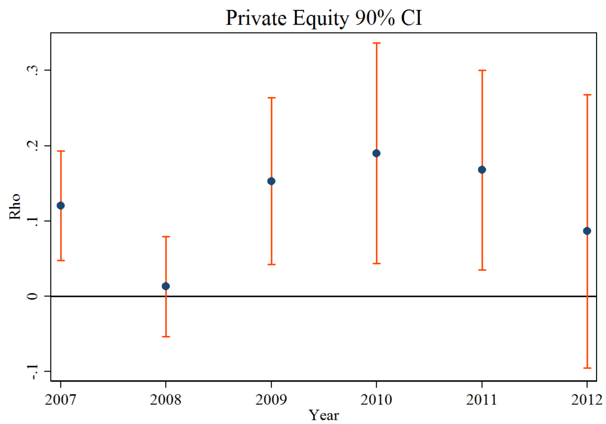
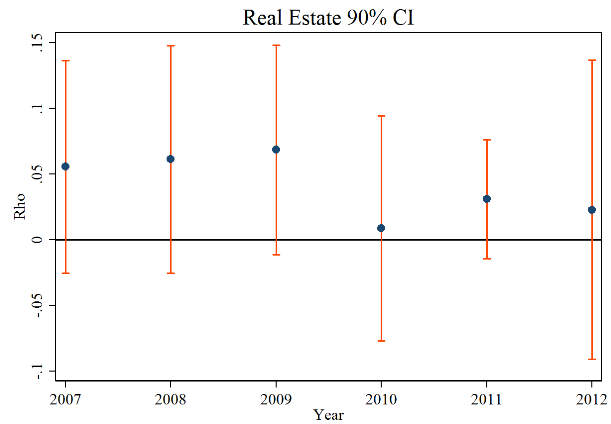


(c)

Figure 5. Herd behavior over time for trustees interconnections.
The figure displays the estimated rho coefficients with the corresponding 90 percent confidence interval from Equation (2): $\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds interconnected through trustees.



(a)



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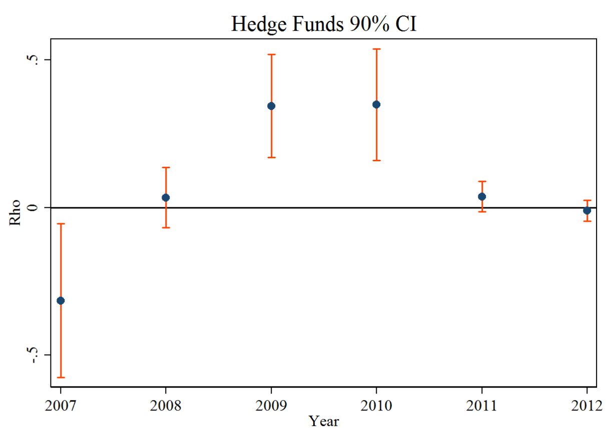

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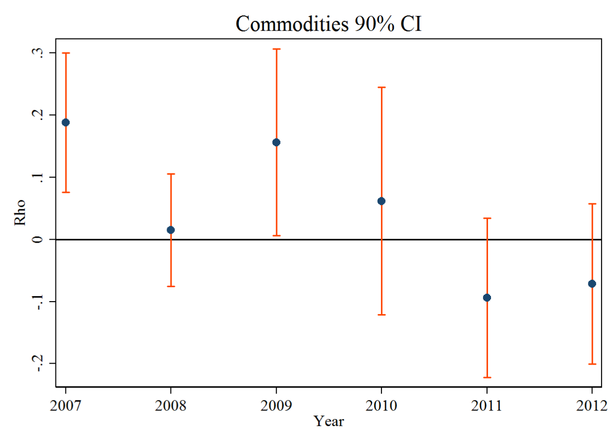
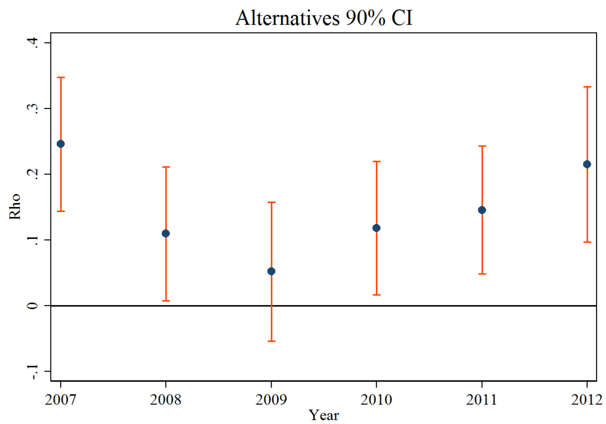
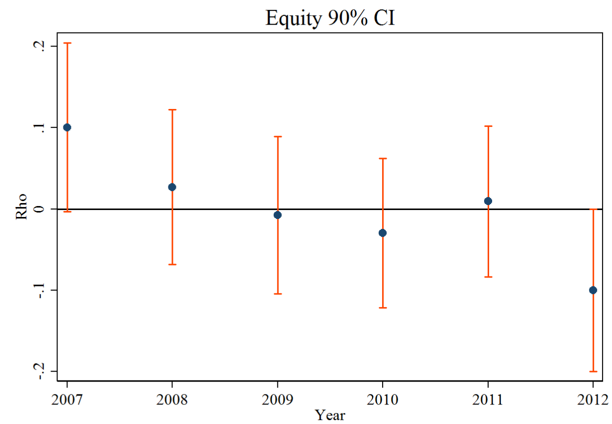


(d)

Figure 6. Herd behavior over time for trustees interconnections by alternative assets. The figure displays the estimated rho coefficients with the corresponding 90 percent confidence interval from Equation (2): $\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. The model is estimated every year over the period 2007 - 2012 on the subsequent five years. Every year the corresponding weighting matrix is used. The results refer to the pension funds connected through trustees.



(a)



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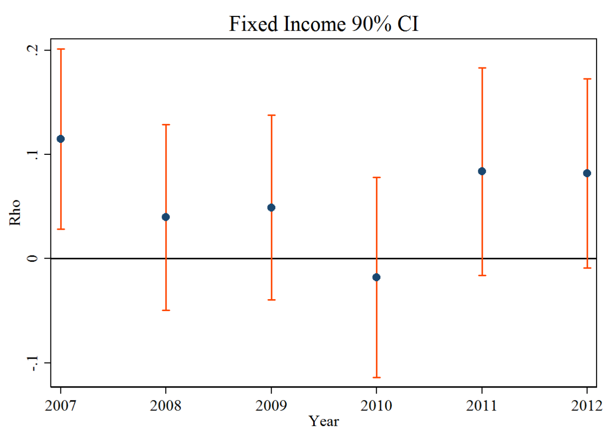
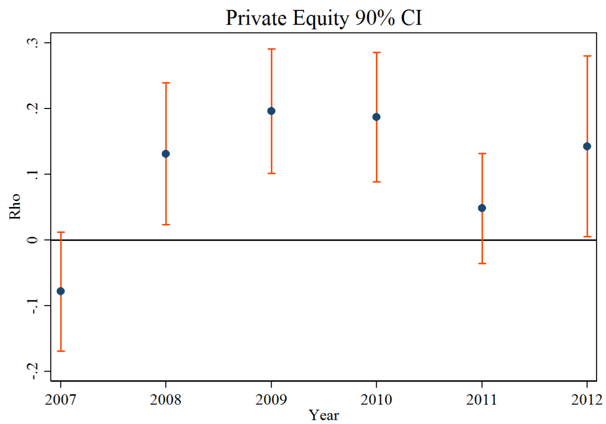


(c)

Figure 7. Herd behavior over time for actuaries interconnections.
The figure displays the estimated rho coefficients with the corresponding 90 percent confidence interval from Equation (2): $\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds interconnected through actuaries.



(a)

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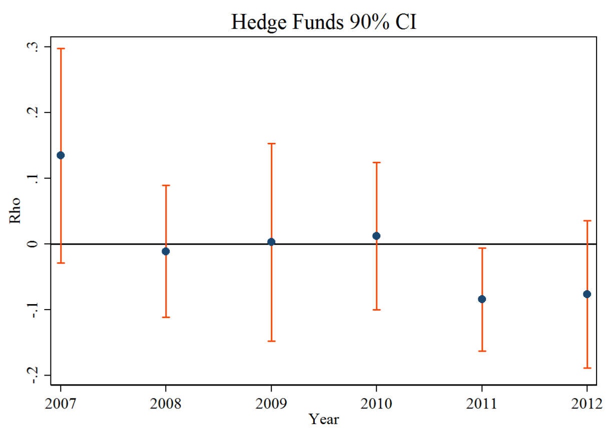

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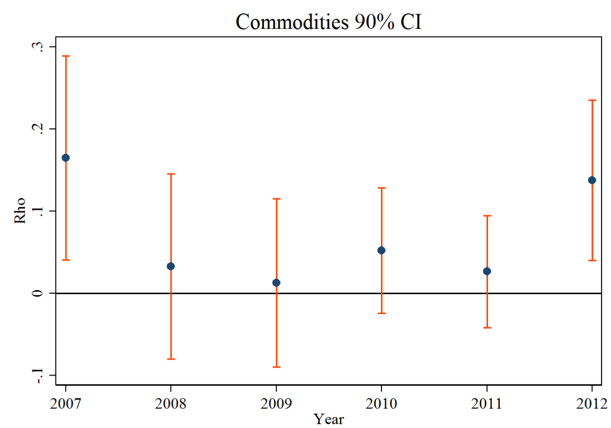

(d)

Figure 8. Herd behavior over time for actuaries interconnections by alternative assets. The figure displays the estimated rho coefficients with the corresponding 90 percent confidence interval from Equation (2): $\mathbf{y}_t = \rho\mathbf{W}\mathbf{y}_t + \mathbf{X}_t\beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds interconnected through actuaries.

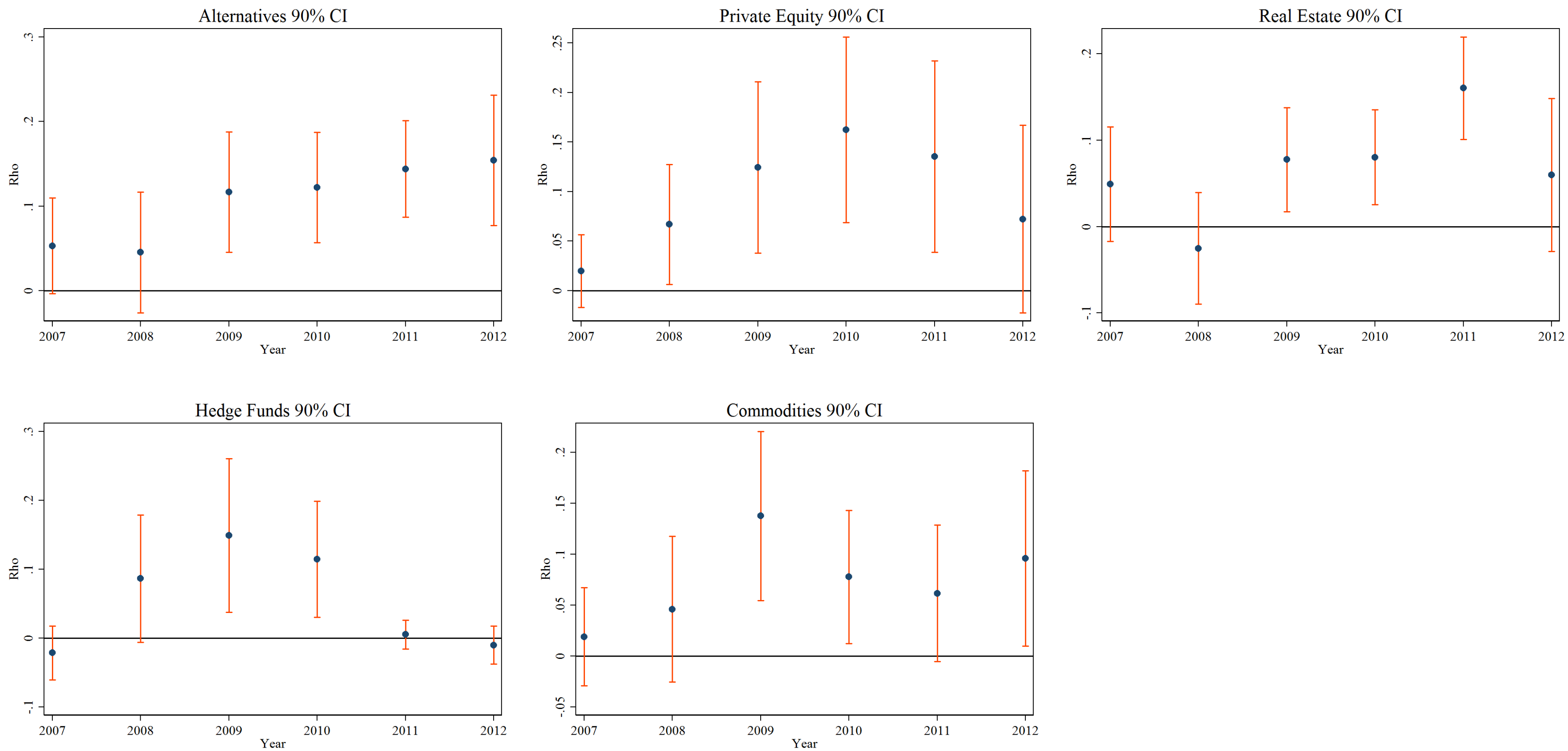

Figure 9. Herd behavior over time for advisory actuaries interconnections by alternative assets.
The figure displays the estimated rho coefficients with the corresponding 90 percent confidence interval from Equation (2): $\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds interconnected through advisory actuaries only.

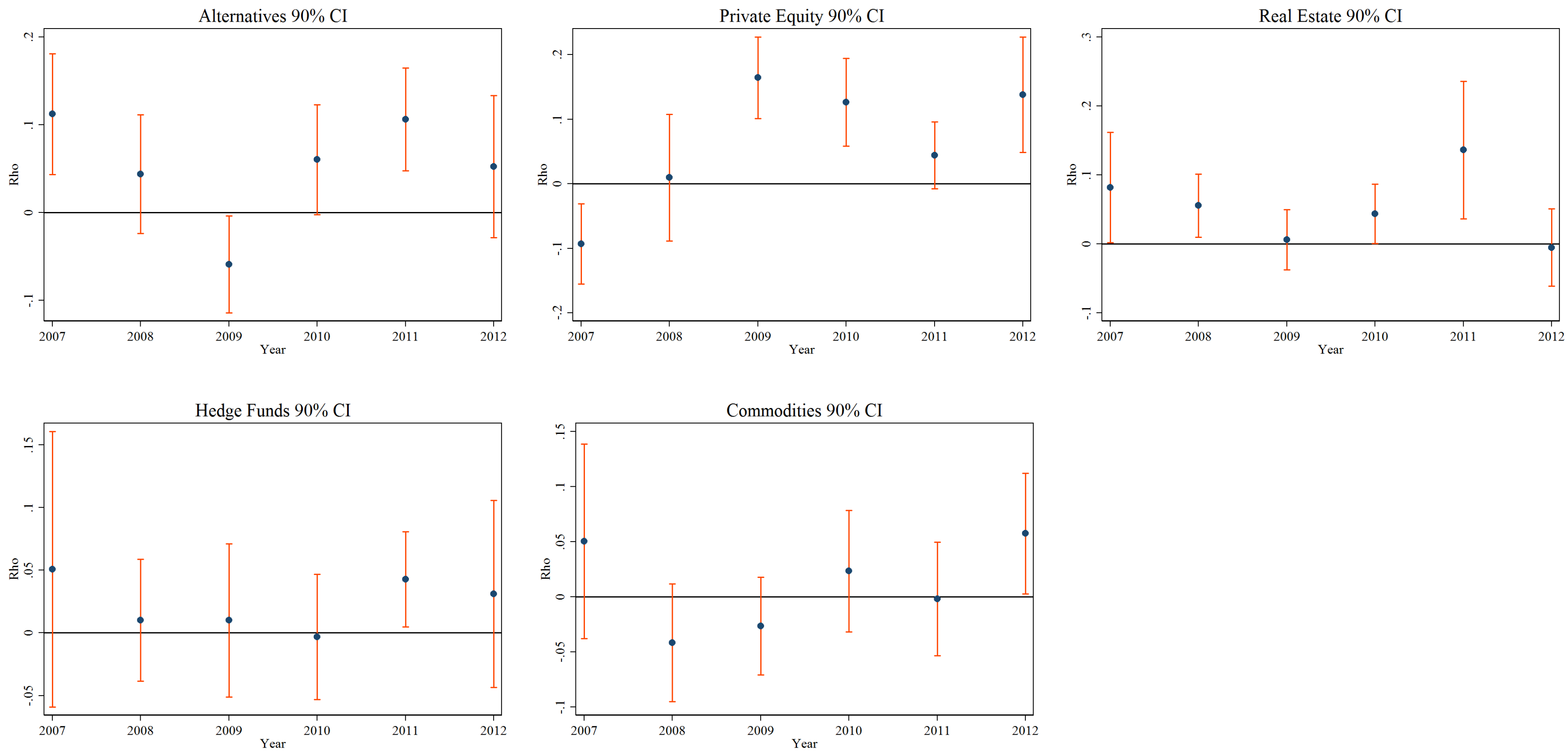

Figure 10. Herd behavior over time for certifying actuaries interconnections by alternative assets.
The figure displays the estimated rho coefficients with the corresponding 90 percent confidence interval from Equation (2): $\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds interconnected through certifying actuaries only.

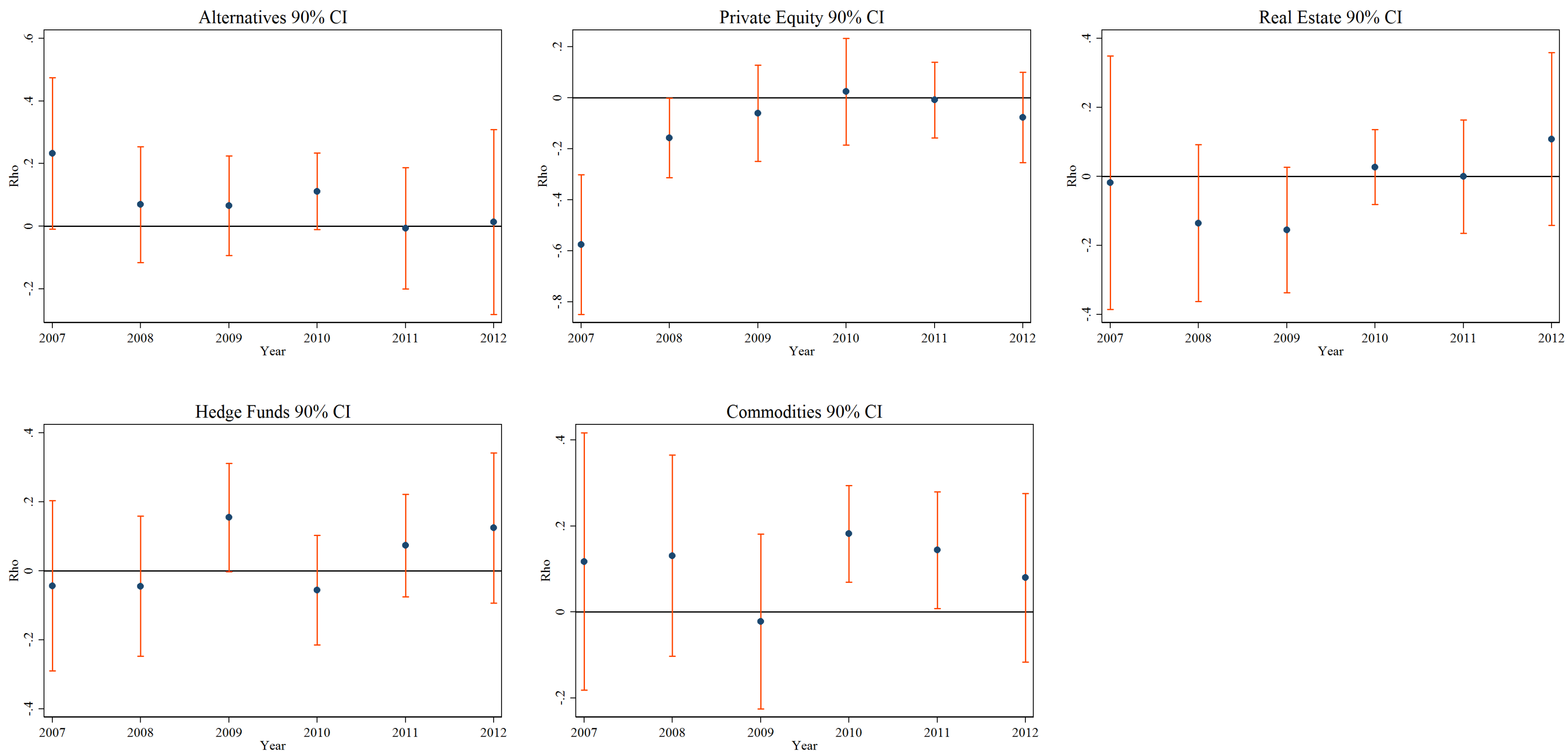

Figure 11. Herd behavior over time for advisory actuarial firms interconnections by alternative assets.
The figure displays the estimated rho coefficients with the corresponding 90 percent confidence interval from Equation (2): $\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds interconnected through advisory actuarial firms only.

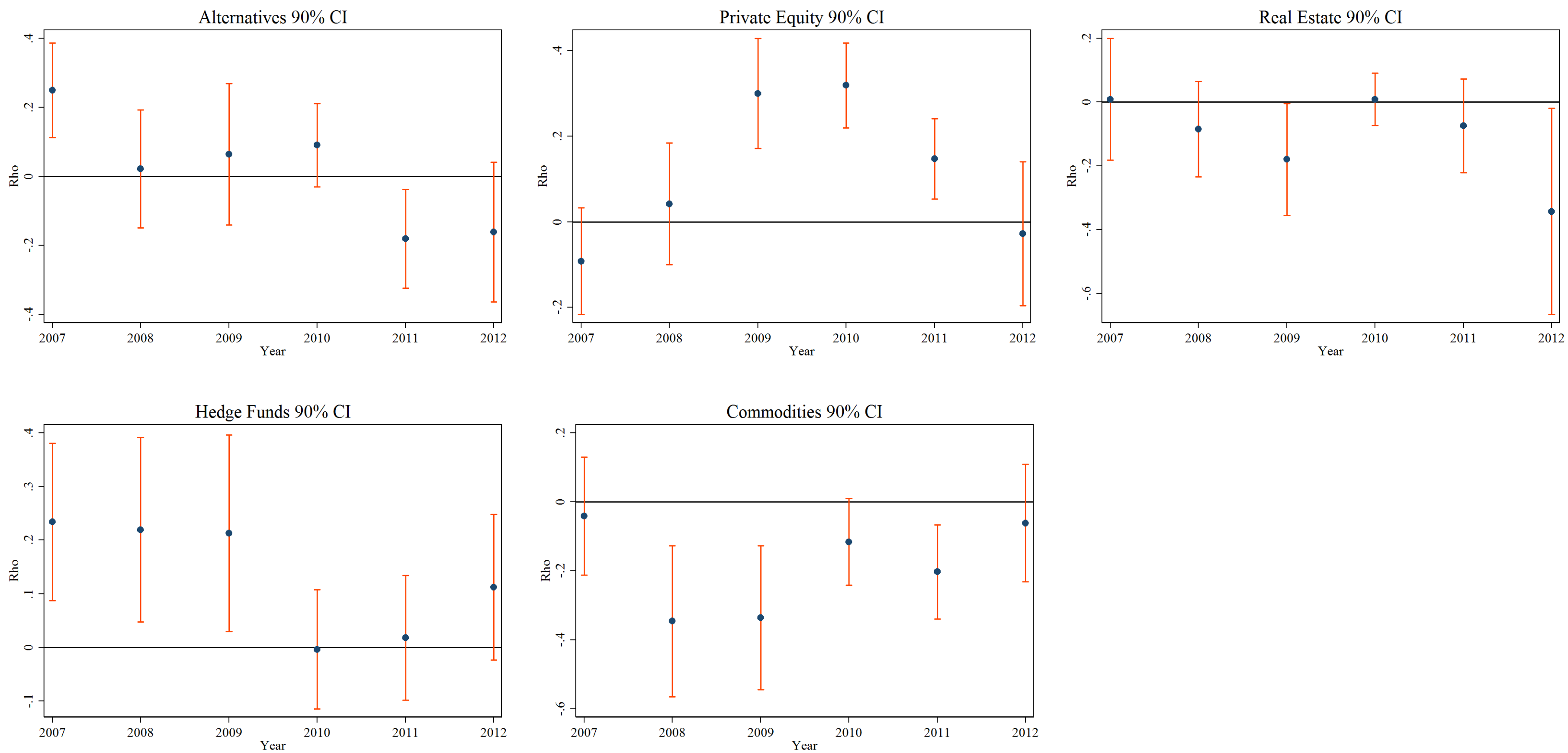

Figure 12. Herd behavior over time for certifying actuarial firms interconnections by alternative assets.
The figure displays the estimated rho coefficients with the corresponding 90 percent confidence interval from Equation (2): $\mathbf{y}_t = \rho\mathbf{W}\mathbf{y}_t + \mathbf{X}_t\beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds interconnected through certifying actuarial firms only.

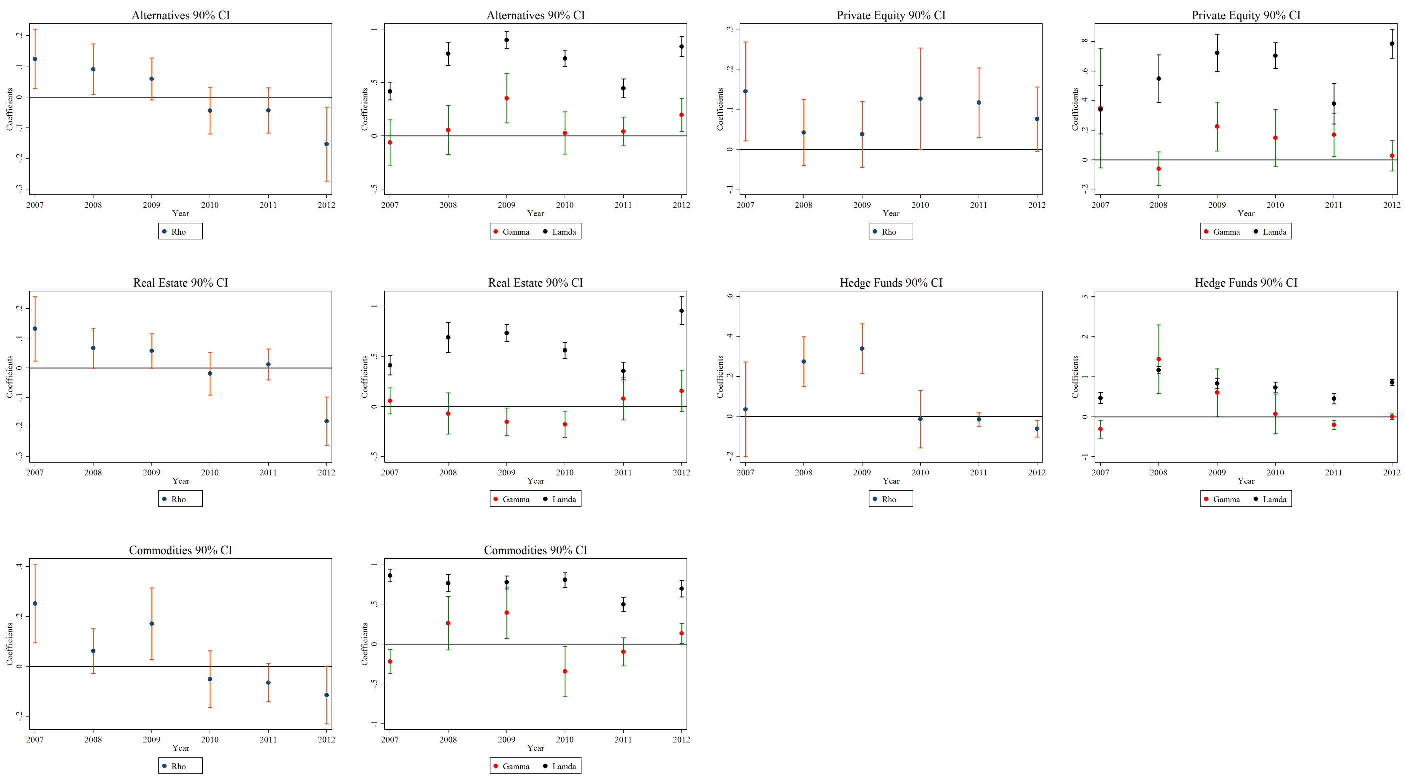

Figure 13. Dynamics in SAA decisions of pension funds interconnected via trustees.
The figure displays the estimated coefficients rho, lambda and gamma with the corresponding 90 percent confidence interval from Equation (3): $\mathbf{y}_t = \lambda \mathbf{y}_{t-1} + \rho \mathbf{W} \mathbf{y}_t + \gamma \mathbf{W} \mathbf{y}_{t-1} + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$. $\mathbf{W}\mathbf{y}_{t-1}$ contains the strategic portfolio weights of interconnected pension funds the year before. $\mathbf{W}\mathbf{y}_t$ is the spatially lagged variable, and $\mathbf{X}_t$ is the usual set of control variables. Also, this model is estimated including pension fund and year fixed effects. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds connected through trustees.

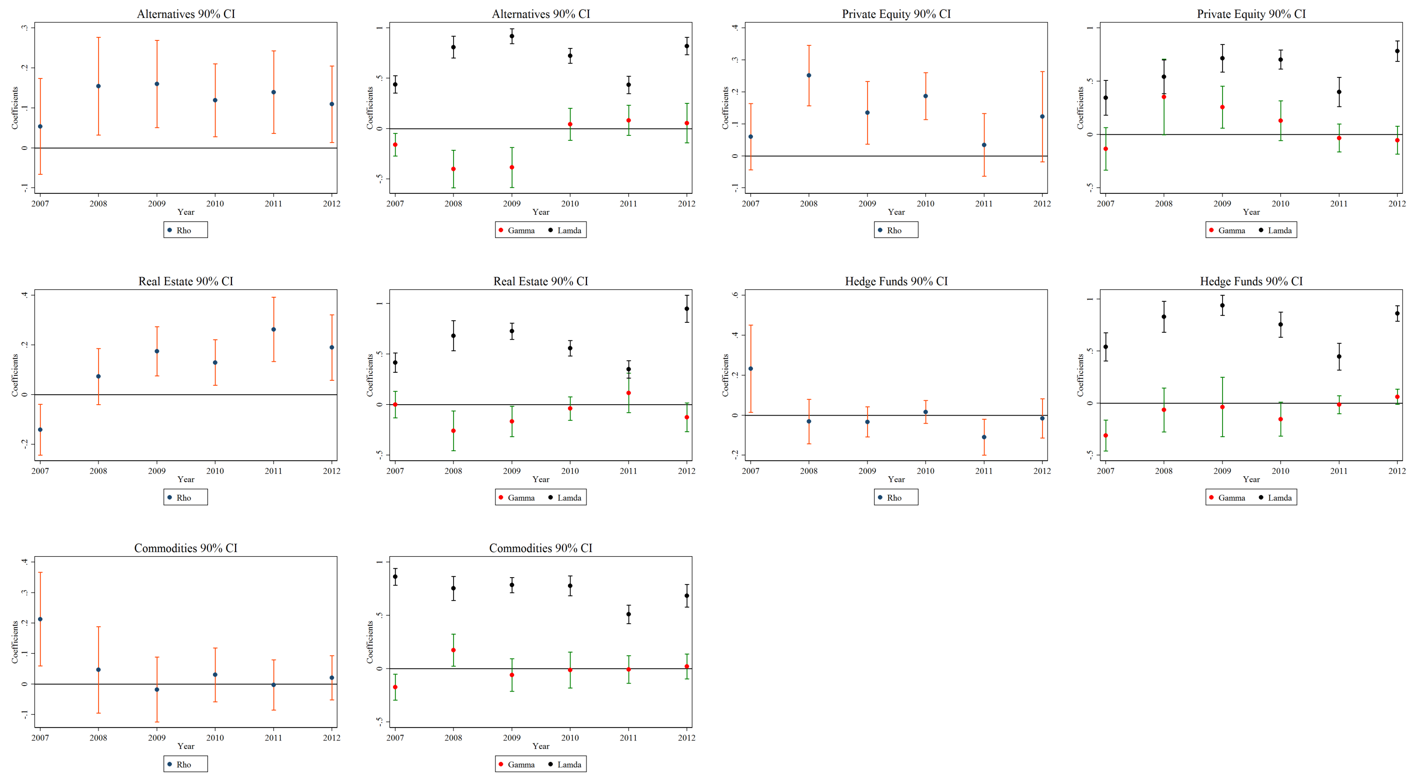

Figure 14. Dynamics in SAA decisions of pension funds interconnected via actuaries.
The figure displays the estimated coefficients rho, lambda, and gamma with the corresponding 90 percent confidence interval from Equation (3): $\mathbf{y}_t = \lambda \mathbf{y}_{t-1} + \rho \mathbf{W}\mathbf{y}_t + \gamma \mathbf{W}\mathbf{y}_{t-1} + \mathbf{X}_t\beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$.$\mathbf{W}\mathbf{y}_{t-1}$ contains the strategic portfolio weights of interconnected pension funds the year before. $\mathbf{W}\mathbf{y}_t$ is the spatially lagged variable, and $\mathbf{X}_t$ is the usual set of control variables. Also, this model is estimated including pension fund and year fixed effects. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds connected through one of the two actuaries.

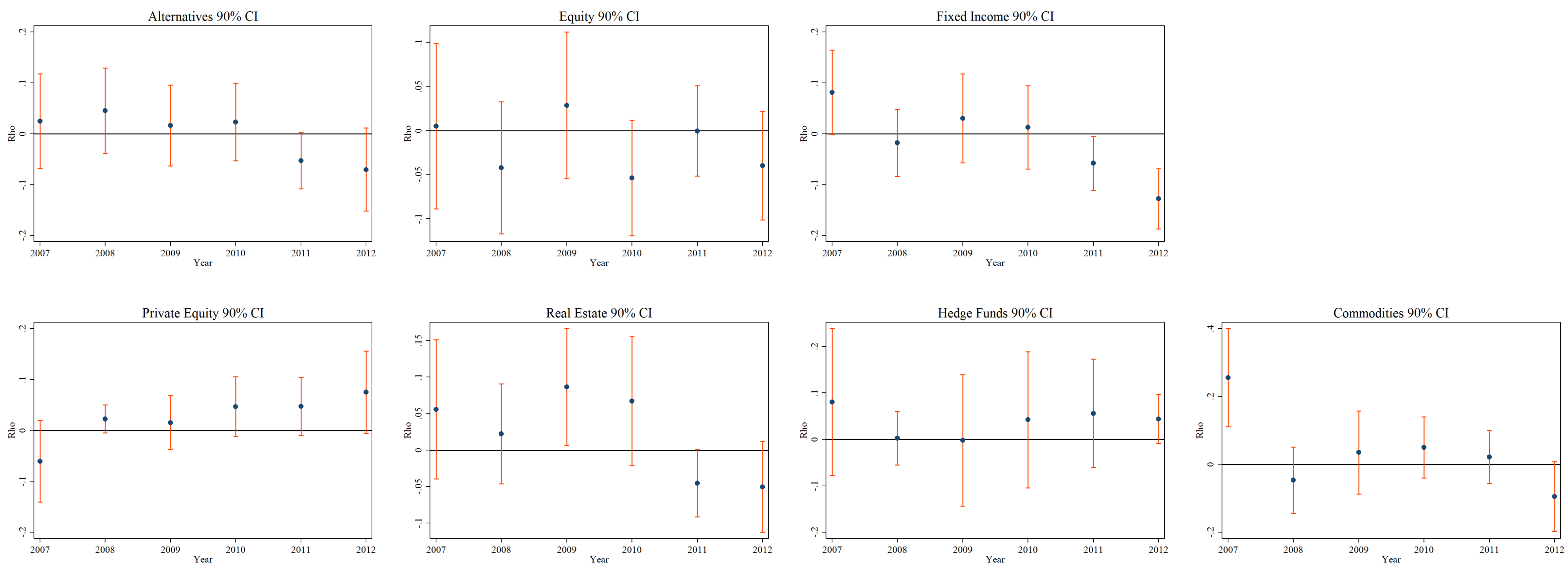

Figure 15. First difference SAA for pension funds interconnected through trustees.
The figure shows the estimation results for the spatial panel autoregressive model $\mathbf{\Delta y}_t = \rho \mathbf{W} \mathbf{\Delta y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$ (Equation 4). The vector of dependent variables $\mathbf{\Delta y}_t$ contains the changes in the strategic asset allocation to each asset class of each pension fund between year t and year $t-1$. ρ is the coefficient that describes the spatial correlation among the changes in the strategic portfolios of interconnected pension funds over time. $\mathbf{W}$ is the spatial weighting matrix that identifies the network of trustees. $\mathbf{X}_t$ contains a set of control variables: funding ratio, size, and the liability duration of each pension fund. $\boldsymbol{\mu}$ and $\boldsymbol{\theta}_t$ indicate pension funds' individual heterogeneity that is fixed over time and the year fixed effect. We estimate the model for each asset class separately and report the corresponding spatial coefficients. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds connected through trustees.

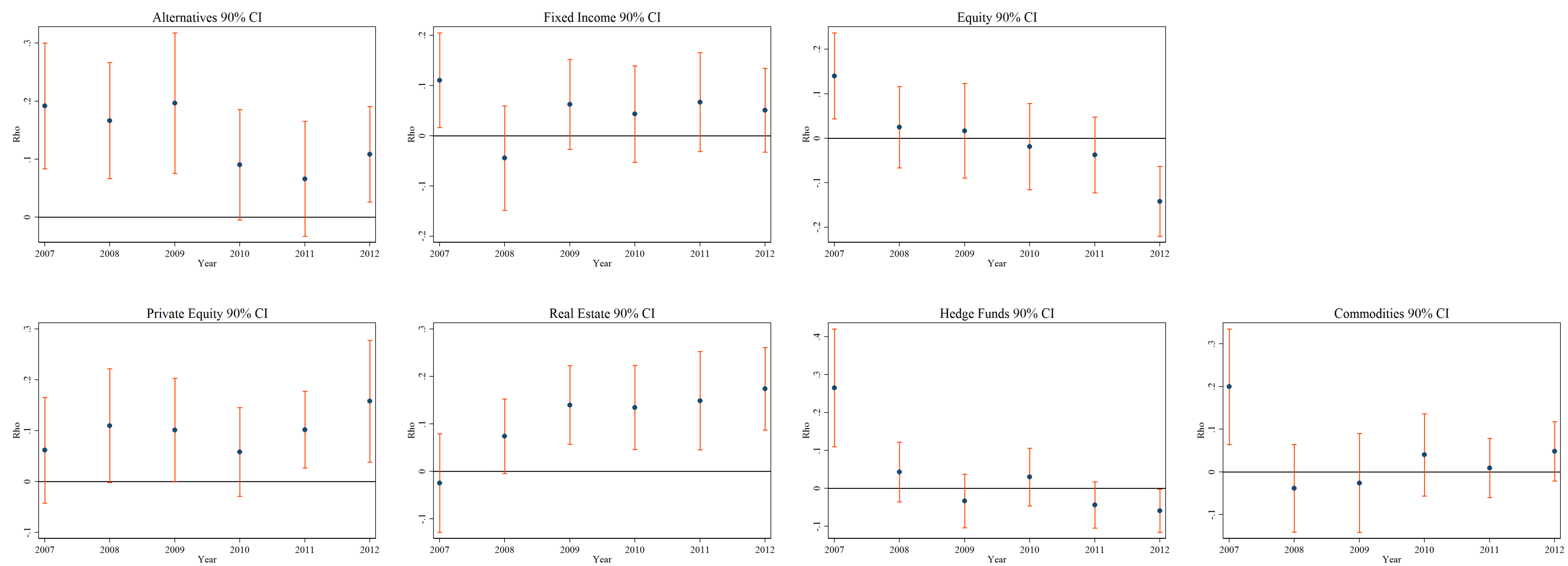

Figure 16. First difference SAA for pension funds interconnected through actuaries.
The figure shows the estimation results for the spatial panel autoregressive model $\mathbf{\Delta y}_t = \rho \mathbf{W} \mathbf{\Delta y}_t + \mathbf{X}_t \beta + \boldsymbol{\mu} + \boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t$ (Equation 4). The vector of dependent variables $\mathbf{\Delta y}_t$ contains the changes in the strategic asset allocation to each asset class of each pension fund between year t and year $t-1$. ρ is the coefficient that describes the spatial correlation among the changes in the strategic portfolios of interconnected pension funds over time. $\mathbf{W}$ is the spatial weighting matrix that identifies the network of actuaries. $\mathbf{X}_t$ contains a set of control variables: funding ratio, size, and the liability duration of each pension fund. $\boldsymbol{\mu}$ and $\boldsymbol{\theta}_t$ indicate pension funds' individual heterogeneity that is fixed over time and the year fixed effect. We estimate the model for each asset class separately and report the corresponding spatial coefficients. The model is estimated every year over the period from 2007 - 2012 on the subsequent five years. For every year, we use the corresponding weighting matrix. The results refer to the pension funds connected through one of the two actuaries.

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