Pension Funds' Herding*

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This paper uses unique and detailed transaction data to analyze herding behavior among pension funds. We distinguish between weak, semi-strong, and strong herding behavior. Weak herding occurs if pension funds have similar rebalancing strategies. Semi-strong herding arises when pension funds react similarly to other external shocks, such as changes in regulation and exceptional monetary policy operations. Finally, strong herding means that pension funds intentionally replicate changes in the strategic asset allocation of other pension funds without an economic reason. We find empirical evidence supporting all three types of herding behavior in the asset allocation of large Dutch pension funds. Whereas weak herding can contribute to financial stability, strong herding may present a risk for financial stability.

JEL Codes: G11, G23.

1. Introduction

In this paper we use unique and detailed transaction data to analyze herding behavior among institutional investors using a rebalancing model based on Calvet, Campbell, and Sodini (2009) in combination with a spatial estimation approach. Nofsinger and Sias (1999) define herding as a group of investors trading in the same direction

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over a period of time. In order to analyze this thoroughly, we distinguish between weak, semi-strong, and strong herding behavior. Weak herding is related to the information motive in the literature, semi-strong herding to the regulation motive, and strong herding to the reputation motive. We document empirical evidence to support all these types of herding in the asset allocation of large Dutch pension funds. Our findings have potential implications for policymakers who are interested in financial stability. Whereas weak herding can contribute to financial stability, strong herding is a risk for financial stability if pension funds deliberately replicate each other's investment strategies without economic reason. Furthermore, regulators need to be aware that semi-strong herding might imply that pension funds react in a similar way to regulatory changes.

Global asset portfolios of institutional investors, such as pension funds, have grown substantially over the past decades. Economic and financial policymakers around the globe have therefore become increasingly interested in the factors driving the allocation of these assets. One of the main motivations behind asset allocation decisions that receives increasing attention from global policymaking institutes is investor herding behavior. The International Monetary Fund does multiple studies on this phenomenon, e.g., Bikhchandani and Sharma (2001); Papaioannou et al. (2013); Cipriani and Guarino (2014); Jones (2015). Also the World Bank analyzes herding behavior (Raddatz and Schmukler 2011), as well as the Federal Reserve (Chari and Kehoe 2002; Cai, Han, and Li 2012; Chari and Phelan 2014) and the Bank for International Settlements (Borio, Furfine, and Lowe 2001; Nirei, Stamatiou, and Sushko 2012).

A key reason why these institutions study herding is its potential implications for financial stability. The European Insurance and Occupational Pensions Authority (EIOPA) provides evidence that pension funds contribute to financial stability as a result of rebalancing strategies (EIOPA 2016). Since most pension funds aim for a more or less fixed asset allocation within a narrow bandwidth, they typically will buy equities following a period in which the equity allocation decreased. The latter will be driven by relative price effects or exchange rate effects in the prior period(s). Also Bohl, Brzeszczynski, and Wilflin (2009) and Thomas, Spataro, and Mathew (2014) find that institutional investors such as pension funds dampen stock market volatility. The Office of Financial

Research in the United States identifies asset managers' herding as one of the key vulnerabilities to financial stability (Elliot 2014). If asset managers enter, e.g., into fire sales simultaneously, this can have an amplifying effect on asset price volatility. The Bank of England also comments on this phenomenon, relating it to the fact that more and more pension funds delegate the management of their assets to external parties (Haldane 2014). This outsourcing gives rise to the question of whether pension funds' asset allocation decisions are interdependent.

We specifically look at herding behavior among pension funds that, because of their size, are important institutional investors in financial markets. On the one hand, pension funds are long-term investors that are able to pursue an optimal long-term investment strategy to the best interest of the pension fund's beneficiaries. This may also contribute to financial market stability, as pension funds can offer liquidity in times of financial markets stress. On the other hand, pension funds are typically constraint investors, e.g., by the size and the nature of the liabilities, the risk preferences of the key stakeholders, and by external regulation. Pension funds can also feel a constraint from peer-group pressure. They may want to invest closely in line with other pension funds to avoid the reputation risk of having to report strongly deviating investment returns.

This paper distinguishes between three types of herding. We define *weak herding* as the result from the fact that pension funds have similar rebalancing strategies. Most pension funds operate in this way (Calvet, Campbell, and Sodini 2009; Bikker, Broeders, and de Dreu 2010; Gorter and Bikker 2013). This behavior is inherent to the investment strategy of pension funds, and the transactions resulting from the rebalancing strategy are not necessarily a form of herding in the sense that pension funds deliberately mimic the transactions of other pension funds. This unintentional or spurious form of herding occurs because groups face similar decision problems and information sets and make similar decisions (Bikhchandani and Sharma 2001). *Semi-strong herding* arises if pension funds react similar to external shocks, e.g., changes in pension fund regulation. Sias (2004) and Andonov, Bauer, and Cremers (2017), e.g., show that regulation can have a significant impact on pension funds' investment decisions. We define *strong herding* as a case in which pension funds intentionally copy the investment decisions of other pension funds without a distinct economic reason. This could, e.g., be the case if a group of pension funds follow changes in the strategic asset allocation of another pension fund or a group of pension funds. In this type of herding, an informed agent follows the trend even though that trend is counter to his initial information about an asset class (Avery and Zemsky 1998). Strong herding may occur through trustees, actuaries, or asset managers who provide services to multiple pension funds (Bauer, Bonetti, and Broeders 2020). Whereas weak herding can contribute to financial stability, strong herding is a risk for financial stability.

This paper seeks to shed light on herding behavior among Dutch defined-benefit funds. The Dutch pension system is an interesting case study for several reasons. First, it is relatively large in terms of its size: its total assets represent roughly twice the size of the gross domestic product (GDP) of the Netherlands. The investment behavior of these pension funds is therefore of significant importance to financial stability. Second, during the Great Financial Crisis and thereafter, most pension funds in the Netherlands suffered considerable decreases in their funding ratios. Indeed, pension funds' funding ratios (as defined by the ratio of total assets over liabilities) moved largely in tandem. This was fueled by the impact of changes in the term structure of interest rates on the value of the liabilities. But also the assets have been hit in a similar way, as pension funds all have very broadly diversified investment portfolios. Their returns will therefore be very similar.

We examine the extent to which these pension funds follow one another in terms of changing their asset allocation. We use a unique data set from De Nederlandsche Bank (DNB), containing monthly transaction data of large Dutch occupational pension funds across a period from January 2009 until January 2015. To test our hypotheses, we employ an econometric specification based on a rebalancing model in combination with a spatial estimation approach. The latter, although common in the political economy literature (see, e.g., Beck, Gleditsch, and Beardsley 2006; Franzese and Hays 2007), is to the best of our knowledge a novelty in the pension economics literature. This approach enables us to estimate the spatial dependence of pension funds' equity and bond allocations. We also check the robustness of our results using an alternative model specification based on the Error Correction Model (Engle and Granger 1987).

The remainder of this paper is organized as follows. Section 2 reviews motivations in the literature for herding behavior among asset managers. Section 3 introduces the hypotheses that we will test, while section 4 describes our data. In section 5 we lay out the model for our empirical analysis. The results are discussed in section 6. In section 7, we replicate the analysis using an alternative regression model to check for robustness of the obtained results. Section 8 concludes.

2. Motives for Herding Behavior

There is an extensive body of theoretical and empirical literature on institutional herding behavior. Institutional investors may exhibit herding behavior for a number of reasons. Bikhchandani and Sharma (2001) mention three motives for herding behavior: information-based herding, compensation-based herding, and reputation-based herding. We present an almost similar classification of motives, distinguishing between an information motive, a regulation motive, and a reputation motive. Moreover, we apply an ordering to these motives, reclassifying the information motive as weak herding, the regulation motive as semi-strong herding, and the reputation motive as strong herding behavior. Weak herding is unintentional, while strong herding is intentional. All are discussed in more detail below.

2.1 Information Motive (Weak Herding)

We define weak herding behavior as the result from the fact that pension funds have similar rebalancing strategies. Investors typically rely on similar sources of information when they make investment decisions. The information can, for instance, be market signals such as the returns on different asset classes. This can lead to herding behavior, which we classify as weak because it is an unintentional consequence of being exposed to similar information. Typically, pension funds have a rebalancing strategy, by aiming for a fixed asset allocation (Calvet, Campbell, and Sodini 2009; Bikker, Broeders, and de Dreu 2010; Rubbaniy, van Lelyveld, and Verschoor 2012; Gorter and Bikker 2013). Blake, Sarno, and Zinna (2017) report short-term mechanical portfolio rebalancing by U.K. pension funds. Also EIOPA documents that pension funds typically have rebalancing strategies (EIOPA 2016). This way, pension funds counteract changes in the asset allocation due to valuation changes in the different asset classes. Since pension funds are exposed to similar market risks, this results in trades into similar directions. Hence, this unintentional herding occurs because pension funds face similar decision problems and information sets (Bikhchandani and Sharma 2001). For example, Rauh (2006) identifies the dependence of investments for defined-benefit pension plans, particularly when they are financially constrained. Very similar, the rising popularity of "index tracking" also leads to herding behavior among institutional investors. Gleason, Mathur, and Peterson (2004); Chen et al. (2011), and Shek, Shim, and Shin (2018) document herding behavior in the market for exchange traded funds (ETFs).

2.2 Regulation Motive (Semi-Strong Herding)

Semi-strong herding arises if pension funds react similarly to external shocks, e.g., changes in pension fund regulation. Pension funds that are subject to the same regulation may choose similar asset allocations, which can result in herding. If the price of risk in regulation makes some asset classes with specific characteristics more attractive to investors, those investors may have an incentive to adjust their asset allocations in the same way (Sias 2004). On the other hand, regulation can cause investors to dislike some other asset classes with certain characteristics. These preferences or aversions for assets with specific characteristics can be measured from changes in regulation. We classify this as semi-strong herding, because in this case pension funds actively make an investment decision following specific changes in circumstances that relate to them. In the literature some examples can be found of this so-called characteristic herding. Severinson and Yermo (2012) show that the introduction of risk-based solvency standards resulted in an increased demand for government bonds by Swiss insurance companies in 2006. Another example is the shift from equities to bonds by U.K. pension funds due to the introduction of fair value accounting in Financial Reporting Standard 17 (FRS 17) in 2003 (Amir, Guan, and Oswald 2010). In addition, Andonov, Bauer, and Cremers (2017) show that Government Accounting Standards Board (GASB) regulation of U.S. public pension funds favors equity investments, as the level of the liability discount rate is derived from the expected return on assets. U.S. public pension funds can artificially improve their financial position by investing in more risky assets. Of course, the introduction of new accounting or regulatory standards does not necessarily lead to shifts in investors' allocations. For example, Amir, Guan, and Oswald (2010) also find that the introduction of fair value accounting for corporate pensions funds in the United States (Statement of Financial Accounting Standards 158 in 2006) did not have pronounced effects in asset allocations.

2.3 Reputation Motive (Strong Herding)

We define strong herding behavior as a case in which pension funds intentionally copy the investment decisions of other pension funds. Reputation-based or strong herding therefore occurs when pension funds actively react to the investment behavior of others without an economic reason. We distinguish two subclasses: career pressure and peer-group pressure. Scharfstein and Stein (1990) claim that, due to career pressure, managers will "follow the herd" if they are concerned about how others will assess their ability to make judgments. In other words, asset managers may be concerned about their labor market position and therefore may choose to mimic investing behavior of other asset managers. Prendergast and Stole (1996) show that reputation herding can be regarded as an inefficient handling of information due to concerns on the reputation of the investor himself. In an ideal world, every individual would behave like a rational Bayesian, optimally learning about the economic environment by correctly combining new information with prior knowledge and then using this information to maximize value. However, actors deviate from this efficient behavior because they care about their reputation. Moreover, Prendergast and Stole (1996) show that young investment managers want to emphasize their learning capacities by exaggerating the importance of new information, while old managers are less willing to change their behavior based on new information because they do not want to suggest their previous behavior was wrong. Dasgupta, Prat, and Verardo (2011) document that career-concerned asset managers exhibit the tendency to replicate past trades. Moreover, they prove that this has an effect on pricing: dealers take advantage of a manager's reputation motivation by offering trades above expected liquidation values based on available information. Managers typically are willing to pay excessively high prices because they expect a reputation reward. Nofsinger and Sias (1999) show that institutional investors are more prone to herding behavior than individual investors. This could indicate the presence of a labor market incentive among institutional investors.

The second subclass of reputation herding is peer-group pressure. This occurs if the risk-taking behavior of an individual asset manager is affected by the risk-taking behavior of other managers in his peer group (Graham 1999). In this case an asset manager chooses to ignore his private information and mimic the actions of another asset manager. The reputation of the other asset manager is then thought to be superior over the asset manager's private information. In following the herd and neglecting private information, reputation herding is a bit similar to herding on informational cascades. However, reputation herding models have an additional layer of mimicking which results from positive reputation externalities that can be obtained by acting as part of a group (Graham 1999). Investors can infer information from the trades of other asset managers. Banerjee (1992) describes this behavior as rational for an individual investor, as the other investors have relevant information for him. The author, however, shows that the equilibrium is inefficient if all investors use information of others instead of their own.

2.4 Risks and Costs of Herding

Herding behavior has potential consequences for market volatility. A classic example is the creation of price bubbles (Avery and Zemsky 1998; Brunnermeijer and Nagel 2004; Hott 2009). Bubbles can arise when rational investors neglect their own private information because they believe that most other traders have very accurate information, while the latter are in fact poorly informed. Jacklin, Kleidon, and Pfleiderer (1992) show that lack of perfect information by investors about the quality of the information possessed by other traders explains the stock market crash of 1987. Also Bikhchandani, Hirshleifer, and Welch (1992) explain short-term bubbles and bursts from informational cascades that occur when individuals follow the behavior of others without regarding their own information. Investors who decide early may be crucial in determining which way the majority will decide. If it turns out, e.g., when new information arrives, that investors have made a wrong decision, they are likely to start herding in the opposite direction. This increases market volatility (Bikhchandani and Sharma 2001). Hirshleifer, Subrahmanyan, and Titam (1994) analyze under which conditions investors find it more profitable to collect information on stocks that are followed by many investors, instead of comparable stocks that are being ignored by the investor community. These cases in which investors infer information from the trades of other asset managers can lead to strong herding behavior.

Herding behavior comes at a cost. Wei, Wermers, and Yao (2015) show that contrary investors benefit from providing liquidity to herding asset managers by trading against them. Froot, Scharfstein, and Stein (1992) find that in markets with short-term trading there may be information inefficiencies in which positive spillovers arise: in these cases it turns out to be rewarding for short-term investors to herd by focusing "too much" on some types of information, while neglecting other types. The reason is that if more short-term speculators study a given set of information, then more of that information disseminates in the market and, as a consequence, profits increase from obtaining a specific set of information at an early stage.

3. Testable Hypotheses

We focus our analysis on changes in equity and bond allocations of the pension funds in our sample. We test for weak, semi-strong, and strong herding in turn. Weak herding can be assessed by investigating how pension funds rebalance their asset allocation over time. Our first hypothesis is that weak herding exists. Since all pension funds will have some rebalancing policy, we expect to find a spurious relation between pension funds. In addition to that, all pension funds have well-diversified exposures on global equity and bond markets and will experience similar market returns. Rebalancing is primarily driven by past returns. Several papers describe the impact of past returns on asset allocation. Blake, Lehmann, and Timmermann (1999) find evidence of rebalancing under 300 U.K. pension funds aimed to stabilize the actual asset allocation around strategic asset allocation. Rauh (2009) finds that high past equity returns lead to higher equity allocations and consequently lower allocations to bonds and cash for U.S. corporate pension plans. However, the equity allocations do not move as far as they would if there had been no rebalancing, implying that the pension funds have some rebalancing policy. Pennacchi and Rastad (2011) report evidence that U.S. state and local government pension funds increase portfolio risk compared with the liabilities following periods of relatively poor investment performance. Mohan and Zhang (2014) also find that public pension funds take more investment risk after lower investment returns in the previous years. Obviously, rebalancing is not done continuously. In practice, the rebalancing behavior of pension funds allows for so called free-floating. Bikker, Broeders, and de Dreu (2010) describe two forms of free-floating. The first is calendar rebalancing, whereby pension funds rebalance their portfolio back to its strategic weights at regular intervals. The second refers to band rebalancing, whereby pension funds create a bandwidth around the strategic weight of each asset class and rebalance their portfolio if the weight of one asset class breaches its band.

Second, we test for semi-strong herding by testing how pension funds act upon exogenous shocks. We hypothesize that changes in regulation will affect the asset allocation of pension funds in similar directions. From the literature we know that pension fund investments are at least to some extent driven by regulation. We identify key changes in pension regulation and document the change in equity and bond allocations around (the announcement of) the change. The regulatory incentives for Dutch pension funds in our sample are mixed. First, liabilities in defined-benefit plans are valued using the term structure of risk-free market interest rates. This implicitly favors government bonds, swaps, and other fixed-income securities as appropriate asset classes. However, Dutch pension funds typically run an asset-liability mismatch by investing partially in risky assets. The risk premium on these assets can be used to index pension benefits to inflation (Broeders et al. 2014). Second, regulation allows Dutch pension funds to always rebalance their asset allocation toward their strategic portfolio weights. This also holds for pension funds with a funding shortfall, i.e., a funding ratio less than 105 percent. However, in this case pension funds are not allowed to "uprisk." They cannot increase their risk profile in excess of the risk profile of the strategic asset allocation. That would be considered a case of gambling for resurrection.[1] We therefore highlight that Dutch pension funds are not forced by regulation to "de-risk" during financial market stress.

Third, we test for strong herding. We hypothesize that pension funds do not want to underperform vis-à-vis their peers, as they are regularly exposed in the news concerning their funding ratio. Therefore they have an incentive to actively follow changes in the asset allocation of their peers. For this we test if pension funds copy the changes in the strategic investment behavior of other pension funds.

4. Data Description

In this section we first describe the structure of the data in section 4.1. Thereafter, we analyze the risk and return characteristics in section 4.2 and the proxy asset allocation and explanatory variables in section 4.3.

4.1 Structure of the Data

We use monthly transaction data that is sourced from the balance of payments statistics of DNB, which is the Dutch central bank. The primary data used are the pension fund's detailed investment holdings in individual equities and bonds. The holdings are uniquely identified according to their International Securities Identification Number (ISIN). The transaction data show the so-called direct investments of pension funds in securities. Pension funds can, however, also invest indirectly in equities and bonds through investment trusts. We also have ISIN data on the investments of these investment trusts. However, except for the two largest pension funds in the sample, we do not have information on which pension funds invest in which investment trusts. Therefore, only for the two largest pension funds can we merge the investment trusts with the pension fund data. Because of liquidations and mergers of pension funds, the length of sample period of each pension fund varies in the sample, particularly for corporate pension funds.

[1] In 2015 a new Pension Act was introduced. As part of this introduction, pension funds were allowed to increase their risk profile once, under specific solvency conditions.

We do not analyze the ISIN records directly. Instead we use aggregated transaction data for equities, bonds, and investment trusts at the pension fund level. Hence, we aggregate the data for each of the three investment classes $j = \{1, 2, 3\}$, for which the following data entries are available:

1. $PB^j_{i,t}$: position at the beginning of the month,
2. $Pur^j_{i,t}$: purchases during the month,
3. $Sal^j_{i,t}$: sales during the month,
4. $\triangle Pr^j_{i,t}$: price changes during the month,
5. $\triangle FX^j_{i,t}$: exchange rate changes during the month,
6. $\triangle OC^j_{i,t}$: other changes during the month,
7. $PE^j_{i,t}$: position at the end of the month,

with pension fund $i = \{1, 2, \ldots, I\}$ and month $t = \{1, 2, \ldots, T\}$. The data set that we analyze contains $I = 39$ large Dutch pension funds over a period that stretches across $T = 73$ months, from January 2009 until January 2015. After deleting those combinations for which we have no or imperfect data, we end up with an unbalanced panel of $N = 2{,}299$ observations.[2] The deletions are specified in appendix A. The panel covers 18 industry-wide pension funds ("bedrijfstakpensioenfondsen"), 16 corporate pension funds ("ondernemingspensioenfondsen"), and 5 professional group pension funds ("beroepspensioenfondsen"). Industry-wide pension funds provide pension services to a specific sector or industry, including public sectors. Industry-wide pension funds are typically mandatory. Corporate pension funds operate for a single company. A professional group pension fund is organized for a specific group of professions such as doctors and pharmacists. The data set covers more

[2]Both the first months and the last months contain all $I = 39$ pension funds. Hence, there is no bias concerning the existence of the pension funds in the data set that we analyze.

than 70 percent of total assets under management in the Dutch occupational pension sector.

The values in entries 1 through 7 satisfy two basic rules. First, the market value of the position at the end of this month equals the position at the beginning of the next month, so

$$PE^j_{i,t} = PB^j_{i,t+1}. \tag{1}$$

Second, the entries in 1 through 7 comply to the following identity relation for each period:

$$PE^j_{i,t} = PB^j_{i,t} + Tr^j_{i,t} + \triangle Pr^j_{i,t} + \triangle FX^j_{i,t} + \triangle OC^j_{i,t}, \tag{2}$$

where the net transactions $\left(Tr^j_{i,t}\right)$ is the difference between the sales and the purchases during the month

$$Tr^j_{i,t} = Sal^j_{i,t} - Pur^j_{i,t} \tag{3}$$

and the other changes $\triangle OC^j_{i,t}$ are reserved for reporting errors that may occur. The position in bonds includes accrued interest.

4.2 Risk, Return, and Benchmark Comparison

As a first step in our analysis, we calculate the returns and risks for the different asset classes and compare those with benchmarks. We are restricted to determining the nominal price return, as we do not have data on cash dividend receipts for equities. Cash dividends received by pension funds are either used to pay pensions or are used to invest in assets. We calculate the money-weighted return on each asset class using the Modified Dietz Method (Dietz 1966), which is given by

$$R^j_{i,t+1} = \frac{PB^j_{i,t+1} - PB^j_{i,t} - \triangle OC^j_{i,t} - Tr^j_{i,t}}{PB^j_{i,t} + w * Tr^j_{i,t}}, \tag{4}$$

whereby we set $w = 0.5$. This means that we assume that transactions are on average executed halfway during the month. Then, we calculate the average weighted return $\bar{R}$ across all pension funds as follows:

$$\bar{R}_t^j = \sum_{i=1}^{I} R_{i,t}^j q_{i,t}^j, \tag{5}$$

which takes the sum of pension funds $i = \{1, 2, \ldots, I\}$ with weights $q_{i,t}^j = \frac{PB_{i,t}^j}{\sum_{i=1}^{I} PB_{i,t}^j}$ based on the investments of pension fund i in asset class $j = \{1, 2, 3\}$ at time t. The average standard deviation of returns is derived similarly to the weighted average across pension funds.

We compare the equity portfolio return with the return on the MSCI World Price Index and the MSCI All Country World Price Index, both in euros. The bond portfolio returns are compared with the JPMorgan EMU Government Bond Index and the JPMorgan Global Bond Index. The statistics of these time series are presented in table 1.

The average monthly equity return is 0.86 percent, which corresponds to an annual price return of 10.82 percent. This shows that the period that we analyze was relatively good in terms of stock market performance. The monthly standard deviation of equity returns is 3.21 percent or about 11 percent annually.[3] The mean of the monthly returns on bonds is 0.24 percent or 2.9 percent annually. The standard deviation of the monthly bond returns is 1.81 percent or 6.27 percent on an annual basis. We find that the mean return and standard deviation of the investment trusts' returns are larger than for bonds and lower than for equity, since investment trusts have both equity and bond holdings.

The time series and corresponding correlations are shown in figure 1. The average weighted return on equity $\bar{R}^{equity}$ is about 85 percent correlated with the MSCI indexes, and the average weighted return on bonds $\bar{R}^{bonds}$ is more than 70 percent correlated with the JPMorgan indexes.

We expect the return per asset class to be closely linked to benchmark returns, as pension funds typically have broad, diversified

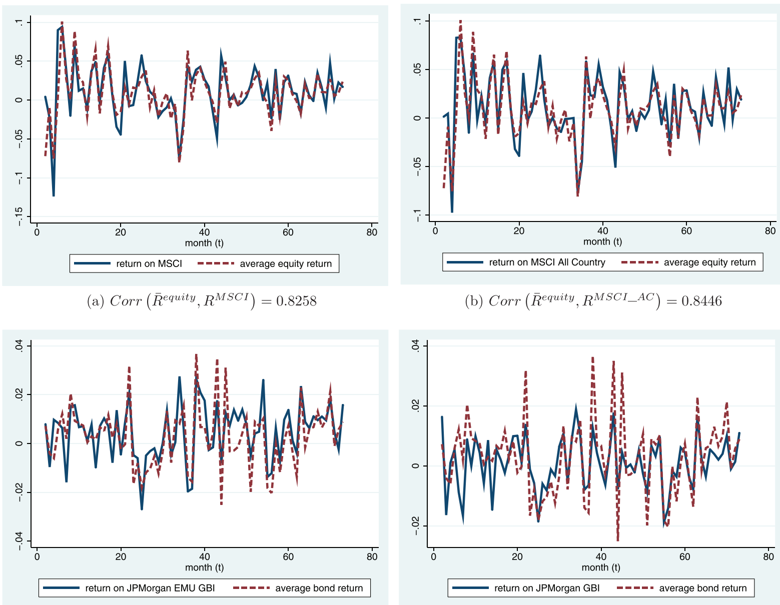
[3]We argue that the relatively low standard deviation of equity returns is a coincidence due to the short period that we analyze.

Table 1. Statistics of the MSCI, JPM EMU Government Bond Index, JPM Global Bond Index, Equity Returns, Bond Returns, and Returns Obtained from Investment Trusts

Variable	Obs.	Mean	Std. Dev.	90%–CI	Min.	Max.
R^{equity}	2,299	.0086	.0321	(−.0400, .0607)	−.1934	.1528
R^{trusts}	2,299	.0058	.0257	(−.0304, .0438)	−.1819	.2043
R^{bonds}	2,299	.0024	.0181	(−.0246, .0319	−.2205	.1518
$\bar{R}^{equity}$	72	.0092	.0317	(−.0513, .0672)	−.0808	.1014
$\bar{R}^{trusts}$	72	.0074	.0255	(−.0199, .0380)	−.1146	.0725
$\bar{R}^{bonds}$	72	.0028	.0126	(−.0188, .0314)	−.0251	.0369
R^{MSCI}	72	.0110	.0345	(−.0460, .0624)	−.1240	.0942
R^{MSCI_AC}	72	.0121	.0334	(−.0471, .0654)	−.0974	.0833
R^{JPM_EMU}	72	.0046	.0113	(−.0168, .0244)	−.0269	.0275
R^{JPM_GBI}	72	.0011	.0086	(−.0165, .0165)	−.0187	.0188

Note: MSCI denotes the MSCI World Price Index, MSCI_AC the MSCI All Country World Price Index, JPM_EMU the JPMorgan EMU Government Bond Index, and JPM_GBI the JPMorgan Global Bond Index.

Figure 1. Time Series and Correlations of the MSCI, JPM Bond Index, Equity Price Returns, and Bond Returns



(a) $Corr\left(\bar{R}^{equity}, R^{MSCI}\right) = 0.8258$ (b) $Corr\left(\bar{R}^{equity}, R^{MSCI\_AC}\right) = 0.8446$

(c) $Corr\left(\bar{R}^{bonds}, \bar{R}^{JPM\_EMU}\right) = 0.7526$ (d) $Corr\left(\bar{R}^{bonds}, \bar{R}^{JPM\_GBI}\right) = 0.7093$

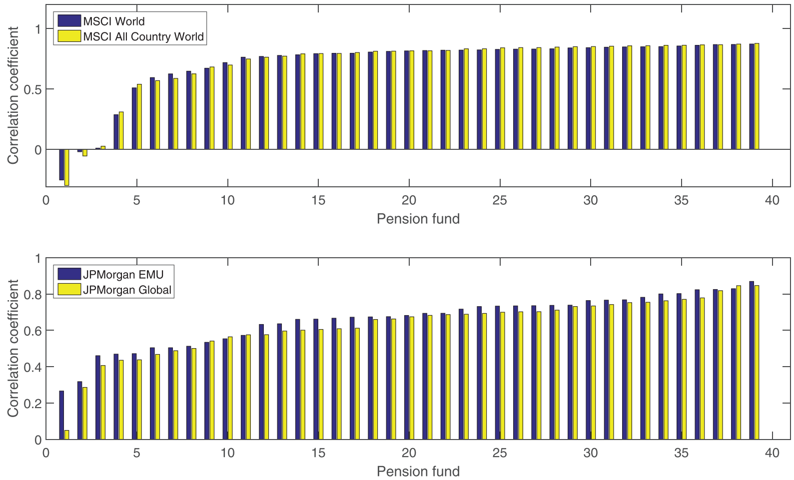
Note: MSCI denotes the MSCI World Price Index, MSCI_AC the MSCI All Country World Price Index, JPM_EMU the JPMorgan EMU Government Bond Index, and JPM_GBI the JPMorgan Global Bond Index.

portfolios and assess their performance relative to a benchmark. The correlations between individual pension fund returns and benchmark returns are shown in figure 2. For most pension funds the correlation coefficient between the price return on the equity portfolio and the MSCI World Price Index returns and the correlation coefficient between the returns on the bond portfolio and the returns on the JPMorgan Index are indeed higher than 50 percent.

4.3 Dependent and Explanatory Variables

The equity and bond allocations are the key dependent variables of interest in our analysis. Table 2 shows the summary statistics of the asset allocations of the pension funds. The mean allocation w^j is

Figure 2. Correlations of the MSCI World Indexes, JPMorgan Bond Indexes, Equity Price Returns, and Bond Returns per Pension Fund



calculated as the equally weighted average direct equity allocation across all pension funds and across time,

$$w^j = \frac{1}{N} \sum_{i=1}^{I} \sum_{t=1}^{T} w^j_{i,t}, \tag{6}$$

for asset class $j = \{1, 2, 3\}$. The mean direct equity allocation is 27.04 percent. This is a proxy for the true equity allocation for two reasons. First, our ISIN data do not include information on pension funds' investments in other asset classes, which are mainly alternative asset classes, such as private equity, direct real estate, hedge funds, and commodities. Second, pension funds can also have indirect equity exposure through investment trusts. The true asset allocation will therefore deviate from the proxy asset allocation presented in table 2. The mean direct allocation to bonds is 46.43 percent. Also this will deviate from the true bond allocation because of the two reasons mentioned before. By construction the three weights add up to one.

If we turn to the explanatory variables, we observe the following. The variable $\log(Assets)$ denotes the natural logarithm of the

Table 2. Summary Statistics

Variable	Obs.	Mean	Std. Dev.	90%–CI	Min.	Max.
w^{equity}	2,299	.2704	.1441	(.0127, .5150)	0	.8476
w^{trusts}	2,299	.2653	.2011	(.0280, .9263	0	.9560
w^{bonds}	2,299	.4643	.1481	(.0570, .6647)	0	.8128
Log $(Assets)$	2,299	15.6764	1.1638	(14.1344, 18.3561)	13.2588	19.7443
$\frac{Actives}{AllParticipants}$	2,299	.3210	.1383	(.0991, .5377)	0	.6528
FR	2,299	1.0910	.1179	(.919, 1.310)	.8	1.57

total assets. This number is below the true log of assets, as again not all asset classes are included in our sample. The ratio of active participants over all participants is an indicator of the maturity of a pension fund. The active participants are the participants that pay contributions to the pension fund. The inactive participants are the retirees plus the so-called dormant members.[4] A dormant or former member is entitled to future pension benefits but is no longer in the service of the employer and therefore does not contribute to the pension fund. The funding ratio FR is the ratio of a pension fund's assets to its liabilities. The latter is the total marked-to-market value of accrued benefit obligations. The minimum required funding ratio by Dutch legislation is roughly 105 percent. However, 37.76 percent of the observations do not satisfy this requirement, due to the weak financial positions of pension funds during the Great Financial Crisis.

5. The Model

In this section we describe the benchmark model of our analysis. The rebalancing model for the asset allocation is introduced in section 5.1. Section 5.2 discusses the changes in the strategic asset allocation. In section 5.3 we extend the benchmark model by a variable which measures the strategic deviations in the asset allocation with respect to other pension funds, depending on their interconnectivity, i.e., we add a spatial estimation approach to our benchmark model.

5.1 Rebalancing Regression Model

Over time, a pension fund's asset allocation will fluctuate around its strategic level. We perform an analysis based on the method applied by Calvet, Campbell, and Sodini (2009). They show that the allocation of a specific asset class can be decomposed into a passive and

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[4]We have the data on the number of participants on a yearly basis only. However, the ratio of active participants over all participants is rather stable over time for each pension fund. Therefore, we interpolate the data to approximate this variable on a monthly basis. Furthermore, the data set contains one so-called closed pension fund, which means that no new participants enter the pension fund. The $\min\left(\frac{Actives}{AllParticipants}\right) = 0$ obtained from our data set concerns this closed pension fund, with non-active participants only.

an active share. The current month's passive share in asset class j is the hypothetical share that would have been obtained if the pension fund had not traded during the last month,

$$w_{i,t}^{j,p} = \frac{w_{i,t-1}^{j}\left(1 + R_{i,t}^{j}\right)}{\sum_{k=1}^{3} w_{i,t-1}^{k}\left(1 + R_{i,t}^{k}\right)}. \tag{7}$$

Then, we derive the passive change as the difference between the current passive share and the last month's actual share,

$$P_{i,t}^{j} = w_{i,t}^{j,p} - w_{i,t-1}^{j}. \tag{8}$$

The active change is given by the actual change minus the passive change,

$$A_{i,t}^{j} = w_{i,t}^{j} - w_{i,t-1}^{j} - P_{i,t}^{j}. \tag{9}$$

Then, we explore to what extent the passive changes explain the active changes, as an estimation for pension funds' rebalancing within a month. However, the returns of the different asset classes determine the asset allocation, not only in the corresponding month but also thereafter. We capture this effect by including the lagged asset allocation $w_{i,t-1}^{j}$ in the model. Hence, we apply the following benchmark equation for pension fund $i \in \{1, 2, \ldots, I\}$, for month $t \in \{1, 2, \ldots, T\}$ and asset class $j \in \{1, 2, 3\}$:

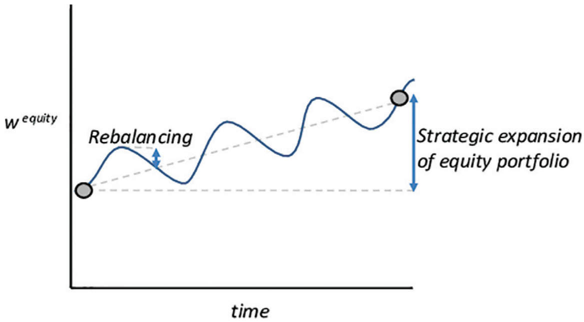
$$A_{i,t}^{j} = \beta_1 P_{i,t}^{j} + \beta_2 w_{i,t-1}^{j} + \beta_3 d\left(Act_{i,t}\right) + \beta_4 d\left(FR_t\right) + \alpha_i + \theta_t + \varepsilon_{i,t}. \tag{10}$$

In this model $d\left(Act\right)$ is the change in the pension fund's share of active participants,[5] $d\left(FR\right)$ is the change in the pension fund's funding ratio,[6] α_i is the pension fund fixed effect, θ_t is the time fixed effect, and $\varepsilon_{i,t}$ is a random error term.

[5]The share of active participants is defined as the number of active members divided by the total number of participants, being active members, dormant members, and pensioners.

[6]There is one missing observation for the funding ratio, which we replace with an approximated value using interpolation.

Figure 3. Graphical Illustration of Rebalancing and Strategic Deviations from an Equity Allocation over Time



5.2 Rebalancing and Changes in the Strategic Asset Allocation

The asset allocations fluctuate over time because of two reasons: (i) pension funds (partially) rebalance in response to the returns of the different asset classes, and (ii) the pension fund's strategic asset allocation changes over time. Figure 3 provides a graphical illustration of the rebalancing effects and the strategic deviations. When the returns on equity are, e.g., relatively high compared with the return on other asset classes, the pension fund can sell equities to buy other asset classes. This process is referred to as rebalancing. If pension funds continuously rebalance their portfolio, the effect under (i) will be completely offset. Continuously rebalancing, however, is costly, and it is not always possible and necessary to immediately respond to fluctuations in the asset returns. Therefore, most pension funds allow the asset allocation to drift between certain limits. For example, a pension fund might allow the equity allocation to fluctuate between 40 and 50 percent. In practice, rebalancing will therefore only be partial. According to Bikker, Broeders, and de Dreu (2010), rebalancing accounts for 39 percent of the portfolio changes. All pension funds are expected to have a rebalancing strategy; otherwise, the actual asset allocation will drift away from the strategic asset allocation. When rebalancing, pension funds make active investment decisions based on similar market information. Rebalancing can therefore be interpreted as a form of weak herding.

It is hard to disentangle the strategic deviations from the rebalancing effects, which are the two effects that cause the changes in the equity allocation. Over the long run, however, deviations in the equity allocation can be considered as a strategic decision of the pension fund's management—see figure 3. Hence, we disentangle changes in the strategic asset allocation from the rebalancing effects by tracking the changes over a long time period. Our measure for changes in the strategic asset allocation is denoted by $Z^j_{i,t} = \frac{w^j_{i,t} - w^j_{i,t-\tau}}{\tau}$. For a large enough time span τ, the fluctuations due to volatile asset returns are smoothed out, such that we mainly measure the changes in the strategic equity allocation. Typically, pension funds review and adjust their strategic asset allocation every three years, with a midpoint of 18 months. We therefore look at τ ranging from 12 to 24 months. If we extend τ further, we would lose too many observations.

5.3 Interconnectivity

The final step in our model is to apply spatial econometric analysis to determine the interconnectivity between pension funds to test for strong herding behavior. For that we use a weighting matrix W of size $[IT \times IT]$ that denotes the spatial distance between pension funds. We define different matrix specifications in order to test herding between pension funds with specific characteristics. For example, we assign weights equal to one in case pension funds are of similar type, have similar share of active participants, or are of similar size. Alternatively we can test whether, for example, the three largest pension funds are market leaders, which holds when they are followed by all others. Hence, for measuring the connectivity of pension funds to their competitors' deviations in the equity and bond allocation, we extend our benchmark model with a spatial relation toward Z, as follows:

$$A^j_{i,t} = \beta_1 P^j_{i,t} + \beta_2 w^j_{i,t-1} + \beta_3 d\left(Act_{i,t}\right) + \beta_4 d\left(FR_t\right) + \beta_5 W_i Z^j_{t-1} + \alpha_i + \theta_t + \varepsilon_{i,t}, \tag{11}$$

whereby W_i denotes the (spatial) weighting matrix, which relates to the changes in strategic asset allocation of the different pension funds.[7] We argue that it is plausible that pension funds observe each other's asset weights, e.g., by quarterly and annual reports.

6. Results

This section discusses the main results from our empirical analysis. First, section 6.1 discusses the results with respect to weak herding. Second, section 6.2 provides a discussion about the findings for semi-strong herding. Finally, we investigate the results for strong herding in section 6.3.

6.1 Weak Herding (Information Motive)

In this section we discuss the results of weak herding. This is based on similar rebalancing strategies across pension funds. The motive for weak herding is based on the fact that pension funds have the same market information and will react similar to this information, as they want stay close to their strategic asset allocation over time. Table 3 presents the results for two specifications of our benchmark model, for both equities and bonds. The first and third column exclude the control variables for the change in active participants and the change in the funding ratio from equation (10). Both models have been specified using a within regression with clustered (by pension fund) standard errors. A Hausman test indicates that a model using unit random effects does not satisfy the corresponding assumptions.

The key observation from table 3 is that the coefficient estimates in the first two rows support rebalancing strategies of pension funds. First, approximately 20 percent of the passive changes in the equity allocation is offset by active changes, while for the bond allocation the active changes offset almost 25 percent of the passive changes. Hence, this implies that pension funds rebalance 20–25 percent of the passive changes during the month by active buying and selling in the asset classes. Second, the coefficient estimates for the asset

[7]We row standardize W, such that the weights per pension fund i at time t add up to one. This means that when pension funds consider the competitors' deviations, they have to divide their attention among the number of competitors. Hence, the assigned weight attributed to each competitor reduces as a pension fund is connected to more competitors.

Table 3. Coefficient Estimates Based on Regression Equation (10)

Dependent Variable $A_{i,t}^j$	j: Equity		j: Bonds	
$P_{i,t}^j$	$-.2053^{***}$	$-.2029^{***}$	$-.2455^{***}$	$-.2454^{***}$
	(.0538)	(.0539)	(.0543)	(.0544)
$w_{i,t-1}^j$	$-.0171^{***}$	$-.0170^{***}$	$-.0211^{***}$	$-.0211^{***}$
	(.0032)	(.0032)	(.0040)	(.0040)
$\mathrm{d}(Act_{i,t})$	—	.0347	—	−.0627
		(.0722)		(.0870)
$\mathrm{d}(FR_{i,t})$	—	−.0110	—	.0054
		(.0109)		(.0131)
Number of Observations	2,149	2,149	2,149	2,149
R^2 – Within	.0737	.0743	.0827	.0831
R^2 – Between	.0097	.0097	.0053	.0034
R^2 – Overall	.0355	.0362	.0381	.0388
Wald Test: Prob. $> \chi^2$	0.0000	0.0000	0.0000	0.0000

Note: Robust standard errors are in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

allocation in the previous period $w_{i,t-1}^i$ is around −2 percent and statistically negative at the 1 percent significance level. Since a high asset allocation in the previous month implies a decline in the corresponding asset allocation in the current month, this finding also shows the tendency of pension funds to rebalance their asset allocation. Both results suggest that pension funds on average rebalance their asset allocation towards a strategic level.

This rebalancing strategy of pension funds contributes to financial market stability, as this implies a buy-low-and-sell-high strategy. If the return on equities is relatively low compared with bonds (and other asset classes), pension funds will buy additional equities. And reversely, if equities performed relatively well, they will sell equities.

Moving on to the two additional explanatory variables in the second and fourth column, we observe that neither the change in the share of active participants nor the change in the funding ratio of pension funds significantly affects equity allocation changes. Since these variables are slowly moving and are likely to exert an effect on the dependent variable over the long term, the monthly deviations are not significantly affected by these effects.

6.2 Semi-strong Herding (Regulation Motive)

Next we turn to the results for semi-strong herding. Changes in regulation can affect the asset allocation of pension funds. This type of herding takes place when investors' preferences (risk appetite) toward asset classes with specific characteristics change following new regulation. We test the prevalence of semi-strong herding among Dutch pension funds by investigating monthly dummy variables. Table 4 shows the dummy variables for which the specified model produces statistically significant coefficients. The cases listed are significant changes in equity or bond allocation simultaneous to or directly following a regulatory change. According to our knowledge, it is in many instances not a priori clear whether it would be optimal to expand or contract the equity or bond allocation as a result of the corresponding event. Also we cannot be sure that the significant time effect comes from the economic and regulatory event around that date. However, on average pension funds appear to react in similar ways, as is demonstrated by the significant time effects around the date of the economic and regulatory event, for which we find multiple examples. Hence, we consider these findings as semi-strong herding, which we discuss below. Notice that the sign of the coefficient, even if significant, does not necessarily indicate whether the corresponding asset allocation on average expands or contracts. It is the average net active change in the asset allocation after correcting for the other variables presented in equation (10).

The main results concern changes in Dutch pension regulation and developments in the Dutch pension system. The first significant time dummy is obtained for May 2009. On May 25, 2009, the Ministry for Social Affairs and Employment (MSAE; this is the ministry responsible for pension fund legislation) announced broad measures in order to tackle the many financial challenges that Dutch pension funds were facing following the financial crisis. It also announced an independent enquiry into pension fund's risk-taking in asset management. When the crisis hit, many pension funds had to incur losses on their investment portfolios, forcing some of them to temporarily cut (previously defined) retirement benefits. It is not unlikely that pension funds viewed the May 2009 announcement as a starting point for regulations that favored de-risking, which would reduce potential losses but also decrease the likelihood that retirees be

Table 4. Coefficient Estimates for Monthly Period Dummy Variables with January 2015 as Reference Date Based on Regression Equation (10)

Year	Month	Equity Allocation	Bond Allocation	Relevant Economic and Regulatory Event(s)
2009	May	.0016	−.0047*	Ministry of Social Affairs and Employment announces broad measures to tackle financial challenges of the Dutch pension system
		(.0022)	(.0026)	
	Jul	.0042**	−.0055**	
		(.0021)	(.0025)	
	Aug	.0064***	−.0083***	
		(.0023)	(.0027)	
2010	Feb	−.0008	−.0064**	Publication of the report of Commission Goudswaard and Commission Frijns
		(.0020)	(.0025)	
	Sep	.0018	−.0042*	European Parliament approved legislation allowing establishment of European Supervisory Authorities
		(.0021)	(.0025)	
	Oct	−.0012	−.0047*	
		(.0021)	(.0025)	
2011	Jan	−.0011	−.0045*	
		(.0020)	(.0025)	
	Feb	.0037*	−.0027	EIOPA established and EIOPA regulation enters into force
		(.0020)	(.0024)	
	Mar	−.0043**	.0039	
		(.0020)	(.0024)	
2013	Mar	.0030	−.0061**	Benefit reductions for insolvent pension funds
		(.0021)	(.0025)	
2014	Mar	−.0045**	.0031	
		(.0022)	(.0025)	Commission Parameters publishes second report
	Apr	.0025	−.0042*	
		(.0021)	(.0025)	
	Dec	.0004	−.0044*	Dutch legislation on adjustment of the financial assessment framework for pension funds adopted
		(.0021)	(.0025)	

Note: Robust standard errors are in parentheses; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

compensated for inflation. In this regard, the equity allocation hike in July and August might be in anticipation of stricter regulation of risky investments.

In February 2010, the report of Commission Goudswaard on the long-run financial sustainability of Dutch occupational funded pensions and the report of Commission Frijns on pension funds' investment were published. Also, the so-called Commission Parameters (an independent advisory committee established by the MSAE) published its second report in March 2014. One of the changes in this second report was a reduction in the expected return on equities. These parameters are used by pension funds in making long-term stochastic projections of their funding ratios. They are also used in setting the contribution policy. In April 2013, many pension funds were forced to reduce the pension rights of their participants to fulfill the recovery requirements, which is followed by a significant change in the bond allocations in March 2013. Finally, in December 2014, some adjustments in the financial assessment framework for pension funds were adopted. EIOPA is the supervisory authority for Institutions for Occupational Retirement Provision (IORP). We observe significant changes in the asset allocations during January 2011 to March 2011, which is immediately after the establishment of EIOPA and after its regulation entered into force. Also in September and October 2010, we obtain a significant change in the bond allocations, around September 22, 2010, when the European Parliament approved the legislation allowing the establishment of the European Supervisory Authorities.

Finally, there are some periods in which relevant changes in regulation did not lead to significant time effects in the aggregate asset allocation of Dutch pension funds. For example, the ultimate forward rate (UFR) for pension funds, affecting the discount rates for long-term liabilities, was introduced in October 2012. Nonetheless, no significant changes in equity or bond allocations are found around that introduction.

6.3 Strong Herding (Reputation Motive)

A final motive driving institutional herding behavior is reputation. Following the argumentation of peer-group pressure, we would expect the risk-taking behavior of a pension fund to be partly dependent on the risk-taking behavior of other pension funds. In other words, pension funds follow the asset allocation of one another. We call this strong herding, as this motive suggests a direct link between the behavior of different actors, rather than an indirect one through common exposure to information or regulation.

We test the hypothesis of the reputation motive by identifying the existence of spatial correlation between changes in pension funds' strategic allocations in asset class j, which is measured by $Z^j_{i,t} = \frac{w^j_{i,t} - w^j_{i,t-\tau}}{\tau}$ for a sufficiently large time span τ. Hence, we take $Z^j_{i,t-1}$ as our measure for strategic changes in the equity or bond allocation of pension funds, which may potentially be followed by other pension funds. Choosing an appropriate time frame to test the spatial effect of the asset allocation is key. Typically pension funds review and adjust their strategic asset allocation every three years, with a midpoint of 18 months. We therefore capture the strategic deviations in the equity and bond portfolio of a pension fund by tracking the changes over 12, 15, 18, 21, and 24 months. In addition, we specify four different connectivity matrices, which allows us to test alternative channels (based on different ways to measure similarity between funds) of herding between pension funds in our data set.

A complicating factor in establishing a relationship between active changes in the asset allocation (our dependent variable) and the change in strategic asset allocation of other pension funds is the fact that pension funds tend to rebalance their asset portfolios over time. A change in the composition of asset portfolios may therefore be the result of the fact that a pension fund is merely rebalancing its portfolio to align it with a strategically chosen asset mix. We have no strong prior as to the length of the time horizon across which rebalancing is the strongest. However, we consider it unlikely that this time horizon exceeds 12 months given the regulatory cycle to which Dutch pension funds are exposed. Still, even when some funds rebalance over a longer period of time, this effect should diminish the spatial effect (which is positive according to our hypothesis), not strengthen it.

Table 5 contains the results of this analysis, which are based on the model as described in equation (11). Hence, we use the

Table 5. Coefficient Estimates for the Spatial Lags $Z^j_{i,t-1} = \frac{w^j_{i,t-1} - w^j_{i,t-1-\tau}}{\tau}$ Based on Regression Equation (11)

	Connected with Three Largest Funds	Connected for Similar Fund Size	Connected for Similar Fund Type	Connected for Similar Fund Age
		j = *Equity*		
$\tau = 12$	1.8909**	.0593	−.1052	.1461
	(.8608)	(.1173)	(.1199)	(.0931)
$\tau = 15$	−.2084	.3499**	−.1116	.0956
	(.9013)	(.1479)	(.1380)	(.1118)
$\tau = 18$	1.9129**	.4667**	−.0775	.0953
	(.8512)	(.1937)	(.1510)	(.1240)
$\tau = 21$	.9180	.3556	−.0988	.0659
	(1.2872)	(.2535)	(.1831)	(.1601)
$\tau = 24$	1.3997	−.0220	.0623	−.0467
	(1.2098)	(.2734)	(.2164)	(.1766)
		j = *Bonds*		
$\tau = 12$	.2903	.2788**	−.0659	.0107
	(.3536)	(.1123)	(.1391)	(.1460)
$\tau = 15$	−.0366	.1088	−.0314	−.2267
	(.3884)	(.1312)	(.1694)	(.1768)
$\tau = 18$	.1122	.0273	.1536	−.2266
	(.5047)	(.1590)	(.1942)	(.2291)
$\tau = 21$	1.3159**	−.1168	−.0710	−.3791
	(.6345)	(.1878)	(.2208)	(.2405)
$\tau = 24$	.9294*	−.2910	.3958	−.4286
	(.5636)	(.2165)	(.2506)	(.2827)

Note: Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

same estimator (fixed-effects regression with cluster-robust standard errors) and include all explanatory variables included in that model. Yet, for the sake of parsimony, only the spatial lag coefficients are displayed in the table. The columns feature four spatial lags based on the following connectivity matrices. In the first column, all pension funds are connected to the three largest pension funds in terms of assets under management. In the second column, pension funds are only connected to other pension funds when they are of similar size (also measured by assets under management). We distinguish between small, medium-sized, and large pension funds, where the thresholds between these categories are at 3 billion and 9 billion euros, respectively. This way, each of the three categories represent roughly a third of the data set. In the third column, pension funds are connected only to the same "type" of pension funds. We distinguish between three types of pension funds: industry-wide, professional group, and corporate pension funds. The fourth column connects pension funds only to other funds when they have a similar share of active (still working) participants as opposed to retired participants. We distinguish three categories with thresholds at 25 percent and 40 percent active participants. Again, this results in roughly equally sized categories. Finally, none of the connectivity matrices allow for pension funds to be connected to themselves, which is indicated by setting the corresponding weights in W equal to zero. To the extent that pension funds "follow themselves" (i.e., demonstrate path dependence in their asset allocation), this effect is captured by the lagged asset allocation and pension fund fixed effect which are included in all models as is done in the benchmark model.

Moving to the results, we observe that two of the four columns generate some significant coefficients. Column 2, which contains a spatial lag that is based on fund size similarity, suggests that there is a positive effect over a time horizon of 15 and 18 months for which we find the most robust evidence of strong herding behavior. If pension funds increase their equity allocation over the last 15–18 months with 1 percentage point on average, then pension funds with a similar size typically increase their equity allocation by 0.35 to 0.47 percentage point as well. Both in terms of significance and size, the effect diminishes when the time horizon moves away from these 15–18 months. As discussed above, this could be partly due to rebalancing, but we find it equally likely that pension funds do not change their strategic asset allocation over a shorter period of time.

There is also some (although less robust) evidence that pension funds follow the equity allocation of the three largest pension funds. Given the spatial effects of similarly sized pension funds discussed above, this result is perhaps not surprising. In terms of time horizon, the evidence is found at 12 months, but also at 18 months, as shown in column 2. The significant coefficient estimates are almost equal to 2, meaning that when the three largest pension funds increase their strategic equity allocation by 1 percentage point, the other pension funds overreact with an increase of their equity allocation by almost 2 percentage points.

We found less statistical evidence concerning bond allocations. However, the two cases for which we found strong herding at 5 percent significance level are similar to the cases for the equity allocation.

These results need to be interpreted with care. As already mentioned, it is not possible to perfectly disentangle changes in the strategic asset allocation from the rebalancing effect. Furthermore, it strongly depends on the specification of the connectivity whether strong herding can be identified. This appears not to be the case for the connectivity among pension funds with similar type or similar share of active participants.

7. Robustness Checks

As a robustness check, we perform an alternative analysis in this section. First, we explain the alternative model in section 7.1. Second, we discuss the results with respect to weak herding, semi-strong herding, and strong herding in section 7.2, section 7.3, and section 7.4, respectively.

7.1 Error Correction Model for Changes in the Asset Allocation

We perform an alternative analysis using a slight adoption of the Error Correction Model (Engle and Granger 1987). The asset allocations are again the key interest in our analysis. We cannot reject that the asset allocation is a stationary variable. The test results for unit root of equity and bond allocations are shown in appendix B. This could lead to biased results when left unattended in the analysis. To tackle this issue, we take the changes in the asset allocation $d\left(w_{i,t}\right) \equiv w_{i,t} - w_{i,t-1}$ as the dependent variable, which does satisfy stationarity. The returns of the different asset classes determine the asset allocation, not only in the corresponding month but also thereafter. For the changes in the asset allocation in the corresponding month, we include the returns of the three asset classes, while for the changes thereafter we again include the lagged asset allocation $w^{j}_{i,t-1}$ in the model. Hence, we specify the following model that has similarities with the Error Correction Model:

$$d\left(w^{j}_{i,t}\right) = \sum_{j=1}^{3} \beta_j R^{j}_{i,t} + \beta_4 w^{j}_{i,t-1} + \beta_5 d\left(Act_{i,t}\right) + \beta_6 d\left(FR_{i,t}\right) + \alpha_i + \theta_t + \varepsilon_{i,t}. \tag{12}$$

To replicate the analysis of section 5.3, we also test for strong herding, by extending the regression with a spatial relation to

$$d\left(w^{j}_{i,t}\right) = \sum_{j=1}^{3} \beta_j R^{j}_{i,t} + \beta_4 w^{j}_{i,t-1} + \beta_5 d\left(Act_{i,t}\right) + \beta_6 d\left(FR_{i,t}\right) + \beta_7 W_i Z^{j}_{t-1} + \alpha_i + \theta_t + \varepsilon_{i,t}. \tag{13}$$

7.2 Weak Herding

Table 6 presents the results of our alternative regression model equation (12). Reading the table from top to bottom, the change in equity allocation is obviously positively related to equity returns. This result simply points toward the fact that the equity allocation increases by construction if equity returns are positive. Conversely, and following the same line of reasoning, equity allocation reacts negatively to positive bond and trust returns.

The key insight from table 6 is that the coefficient estimates in the first four rows support rebalancing strategies of pension funds. First, the coefficients of the returns from the three asset classes are

Table 6. Coefficient Estimates of the Benchmark Model Based on Regression Equation (12)

Dependent Variable $d(w^j_{i,t})$:	**j: Equity**		**j: Bonds**	
$R^{equity}_{i,t}$	.1063***	.1063***	−.0410***	−.0414***
	(.0116)	(.0116)	(.0140)	(.0140)
$R^{trusts}_{i,t}$	−.0309***	−.0307***	−.0700***	−.0704***
	(.0085)	(.0085)	(.0102)	(.0102)
$R^{bonds}_{i,t}$	−.0508***	−.0506***	.1163***	.1154***
	(.0153)	(.0154)	(.0185)	(.0185)
$w^j_{i,t-1}$	−.0155***	−.0155***	−.0225***	−.0225***
	(.0032)	(.0032)	(.0041)	(.0041)
d($Act_{i,t}$)	—	−.0055	—	−.0420
		(.0741)		(.0892)
d($FR_{i,t}$)	—	−.0058	—	.0100
		(.0112)		(.0135)
Number of Observations	2,149	2,149	2,149	2,149
R^2 – Within	.3090	.3091	.2601	.2604
R^2 – Between	.0912	.0905	.0010	.0015
R^2 – Overall	.2547	.2549	.2009	.2016
Wald Test: Prob. > χ^2	0.0000	0.0000	0.0000	0.0000

Note: Robust standard errors are in parentheses; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

lower in absolute terms than what we would expect from a "passive strategy," whereby the pension fund does not rebalance, such that the asset allocations are fully determined by the past returns.[8] Hence, the coefficient estimates of the returns from the three asset classes imply that pension funds rebalance during the month by offsetting part of the returns, as confirmed by our results in section 6.1.

[8]Consider the following numerical example. Suppose the equity allocation equals $w^{equity}_{t-1} = 25\%$ and the monthly returns are $R^{equity}_t = 1\%$, $R^{bonds}_t = 0\%$, and $R^{trusts}_t = 0\%$. Then, ceteris paribus, we would obtain $w^{equity}_t = \frac{101\%*0.25}{101\%*0.25+100\%*0.75} = 25.19\%$. Hence, we might expect a coefficient for R^{equity}_t roughly equal to $\frac{25.19\%-25\%}{1\%} = .19$. However, we find a substantial lower coefficient for R^{equity}_t, namely .1063. This means that we need to take all four coefficients into account when we quantify the average extent of rebalancing, as we have done under our benchmark model in section 6.1. The same holds for the other coefficients and for the bond allocation.

Second, we observe that the larger last month's equity or bond allocation is, the more the current month's share is reduced on average. Both results suggest that pension funds on average rebalance their asset allocation toward a desired level, which is in line with our results on weak herding obtained in section 6.1. For the two additional variables $d\left(Act_{i,t}\right)$ and $d\left(FR_t\right)$, we again obtain no significant effect on the dependent variable. Hence, the change in the funding ratio and the change in the share of active members do not affect the changes in the monthly asset allocations.

7.3 Semi-strong Herding

Next we turn to the discussion of the results for semi-strong herding, which are presented in table 7. We find more significant month effects under our alternative model than under our benchmark model. Since there is quite some overlap with the results obtained in section 6.1, we mainly discuss the newly obtained significant time effects.

First, we obtain a significant time effect for March 2009, when pension funds with insufficiently high funding ratios received instructions from the regulator for filing recovery plans. Also, the "Commission Parameters" published its first report defining new parameters in September 2009. Their second report, published in March 2014, again significantly affected asset allocations, with lower equity and higher bond allocations.

Furthermore, several developments in the financial assessment framework for Dutch pension funds, the so-called FTK, took place. For example, in April 2010, a report on the evaluation of the FTK was published, while in May 2012 a letter on the revision of the FTK was released. Both events resulted in significant changes in the next month's asset allocations. In September 2011, MSAE published a report which announced a revision of the standard method for the calculation of risk-based buffers for pension funds. Next, in September 2011, a "Pension Deal" was accepted, which includes an agreement among social partners and MSAE concerning the future of the Dutch occupational pension system.

Unlike the benchmark model, we now find several examples in which the European Central Bank's (ECB's) exceptional monetary

Table 7. Coefficient Estimates for Monthly Period Dummy Variables with January 2015 as Reference Date Based on Regression Equation (12)

Year	Month	Equity Allocation	Bond Allocation	Relevant Economic and Regulatory Event(s)
2009	Mar	−.0032 (.0024)	.0049* (.0029)	Instructions for recovery plans
	Jul	.0051** (.0021)	−.0051** (.0026)	Ministry of Social Affairs and Employment announces broad measures to tackle financial challenges of the Dutch pension system
	Aug	.0050** (.0023)	−.0066** (.0028)	
	Sep	.0000 (.0024)	−.0050* (.0028)	Commission Parameters publishes first report and ECB's launch of the Covered Bond Purchase Program (CBPP1)
2010	Feb	.0006 (.0021)	−.0081*** (.0026)	Publication of the report of Commission Goudswaard and Commission Frijns
	May	.0021 (.0021)	−.0051** (.0025)	Publication of the report on evaluation of FTK and announcement of SMP by ECB
	Aug	−.0030 (.0022)	.0051* (.0026)	No major regulatory event observed
	Oct	−.0040* (.0022)	−.0020 (.0026)	European Parliament approved legislation allowing establishment of European Supervisory Authorities
2011	Jan	−.0010 (.0021)	−.0057** (.0026)	
	Feb	.0049** (.0021)	−.0044* (.0025)	EIOPA established and EIOPA regulation enters into force
	Mar	−.0042* (.0021)	.0042 (.0026)	
	Oct	−.0057** (.0025)	.0069** (.0030)	"Pension Deal" and revision of risk-based capital buffers
	Dec	.0055*** (.0021)	−.0056** (.0025)	Launch of the CBPP2

(*continued*)

Table 7. (Continued)

Year	Month	Equity Allocation	Bond Allocation	Relevant Economic and Regulatory Event(s)
2012	Jul	−.0046**	.0065**	Letter on revision of the FTK
		(.0023)	(.0028)	
	Aug	.0032	−.0050*	OMT announced by ECB
		(.0022)	(.0026)	
2013	Mar	.0045**	−.0077***	Benefit reductions for insolvent pension funds
		(.0022)	(.0027)	
2014	Mar	−.0077***	.0065**	
		(.0022)	(.0027)	Commission Parameters publishes second report
	Apr	.0032	−.0049*	
		(.0021)	(.0026)	

Note: Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

policy affect pension funds' asset allocations. First, the bond allocation is negatively affected by the ECB's first Covered Bond Purchase Program (CBPP1), which started in September 2009. The second Covered Bond Purchase Program (CBPP2), launched in December 2011, again resulted in significantly lower bond allocations. In May 2010, the ECB's Securities Markets Program (SMP) started with purchasing securities. Finally, the Outright Monetary Transactions (OMT) was announced in August 2012. All these programs resulted in a significant contraction of the pension funds' bond allocation.

In addition, we find one example of the situation in which significant changes in equity or bond allocation did not concur with relevant changes in regulation or exceptional monetary policy operations, which holds for the time effect in August 2010. However, this case is only weakly significant.

7.4 Strong Herding

Table 8 presents the results of the spatial analysis under our alternative regression model equation (13). We use the same estimator (fixed-effects regression with cluster-robust standard errors) and include all explanatory variables included in that model. Again, only the coefficients of the spatial lags are presented.

The first column, which contains spatial lags with the three largest pension funds, and the second column, which contains spatial lags based on fund size similarity, provide the only statistically significant evidence on strong herding. For almost all cases which are significant in table 5, we again obtain significant coefficient estimates for the spatial lag at 5 percent significance level under our alternative regression model. Moreover, the strongest evidence is again obtained for the equity allocation over 15 to 18 months for pension funds with similar size. From this result we can conclude that when pension funds increase their equity allocation over the last 15–18 months with 1 percentage point on average, then pension funds with a similar size typically expand their equity holdings by 0.36 to 0.49 percentage point. We can conclude that our results on strong herding are robust to the type of regression model, as we obtain qualitatively the same results as the ones we have obtained in section 6.3.

Table 8. Coefficient Estimates for the Spatial Lags $Z_t = \frac{w^j_{i,t} - w^j_{i,t-\tau}}{\tau}$ Based on Regression Equation (13)

	Connected with Three Largest Funds	Connected for Similar Fund Size	Connected for Similar Fund Type	Connected for Similar Fund Age
		$j = Equity$		
$\tau = 12$	2.0870**	.0388	−.1272	.1033
	(.8900)	(.1213)	(.1239)	(.0963)
$\tau = 15$	−.5247	.3617**	−.1226	.0232
	(.9248)	(.1519)	(.1418)	(.1147)
$\tau = 18$	1.7152*	.4941**	−.1304	.0225
	(.8790)	(.1995)	(.1555)	(.1277)
$\tau = 21$	.4566	.4287	−.1604	−.0444
	(1.3285)	(.2612)	(.1892)	(.1650)
$\tau = 24$	1.1445	.0390	.0322	−.1171
	(1.2454)	(.2814)	(.2228)	(.1818)
		$j = Bonds$		
$\tau = 12$	.2859	.2727**	−.1059	−.0214
	(.3639)	(.1155)	(.1430)	(.1502)
$\tau = 15$	−.0167	.0837	−.0012	−.1765
	(.3941)	(.1331)	(.1719)	(.1797)
$\tau = 18$	.1316	−.0051	.1893	−.2365
	(.5157)	(.1624)	(.1983)	(.2341)
$\tau = 21$	1.4222**	−.1187	−.0571	−.2976
	(.6467)	(.1918)	(.2252)	(.2455)
$\tau = 24$	.9357	−.3027	.3809	−.3704
	(.5721)	(.2203)	(.2543)	(.2878)

Note: Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

8. Conclusion

In this paper we use unique and detailed transaction data to analyze herding behavior among pension funds. We distinguish between weak, semi-strong, and strong herding behavior. Weak herding occurs if pension funds have similar rebalancing strategies. This is unintentional herding based on the fact that pension funds act similar upon market information. Semi-strong herding arises if pension funds react similar to other external shocks, e.g., changes in pension fund regulation. Herding has a regulation motive in this case. Finally, strong herding occurs if pension funds intentionally replicate changes in the strategic asset allocation of other pension funds. In this case herding has a reputation motive. Pension funds may adjust their investment strategy as a result of peer-group pressure without an economic reason.

We find empirical evidence for all three types of herding. In doing so, we use monthly holdings and transaction data of 39 large Dutch pension funds over the period from January 2009 until January 2015. The primary data used are pension funds' detailed investment holdings in bonds, equities, and trusts. These holdings are uniquely identified according to their International Securities Identification Number (ISIN). We aggregate the holdings and transaction data for these three asset classes. We focus the empirical analysis on the equity and bond allocations. We apply a rebalancing regression model to track changes in the equity and bond allocation over time and to measure the spatial distance between pension funds.

Our key findings are the following. Pension funds exhibit weak herding behavior. Pension funds rebalance their asset allocation in the short run and, hence, they react similar to market information. We find robust evidence that more than 20 percent of the passive changes in the equity allocation are offset by active changes during the month. For bonds this rebalancing of the asset allocation accounts for almost 25 percent. Since rebalancing implies a buy-low-and-sell-high strategy, pension funds contribute to financial market stability.

In addition, pension funds demonstrate semi-strong herding behavior. We find multiple examples where pension funds adjust their equity and bond allocations around (the announcements of) changes in pension fund regulation.

Finally, pension funds also display strong herding behavior. The most robust evidence of strong herding is observed for pension funds of similar size over a 15- to 18-month period. If pension funds increase their equity allocation with 1 percentage point on average, then pension funds with a similar size typically increase their equity allocation by 0.35 to 0.47 percentage points with a lag of 15–18 months. The 18-month period is halfway the typical three-year cycle at which the strategic asset allocation is reviewed and adjusted.

As such, our results indicate support for the information, regulation, and reputation motives of herding. We find that our results are robust by replicating the analysis using an alternative regression model. The results from this confirm that pension funds rebalance their asset allocations. Also there is quite some overlap with the results on semi-strong herding. However, we also document evidence of (small) changes in asset allocations in response to exceptional monetary policy operations. Furthermore, we obtain the same qualitative results on strong herding from an expanded model with spatial lags.

Our findings have potential implications for regulators and policymakers who are interested in safeguarding financial stability. Whereas weak herding can contribute to financial stability, strong herding behavior is a risk for financial stability. Regulators need to be aware that semi-strong herding behavior might imply that pension funds react in a similar way to regulatory changes. To prevent a large impact on asset allocations, the regulatory price of risk for different asset classes should be balanced.

Havine said this, there are some points to consider when interpreting the results. First, our holdings and transactions data represent the majority of pension fund investments but exclude alternative asset classes, such as private equity, direct real estate, hedge funds, and commodities. Second, pension funds can also have equity and bond exposures indirectly through the investment trusts. Since we have no detailed information on the holdings and transactions data of the investment trusts, we cannot offer the complete picture on changes in the true asset allocation. In our sample roughly 26.5 percent is allocated to investment trusts. For future research we could extend our analysis by researching herding behavior in specific segments of the equity market, or even in specific stocks and the deployment of derivatives to hedge risks.

Appendix A. Deleted Observations

The raw data contain 2,567 observations. After cleaning the data, the remaining number of observations is 2,299. The following steps show the procedure we followed:

- We drop outliers which do not satisfy the rules from equation (1) and equation (2) with an error over more than 5 percent of the corresponding value (42 observations deleted).
- We drop excessive monthly returns, specifically if they exceed 25 percent (7 observations deleted).
- We drop observations when in a single month the equity or bond allocation sharply increases (> 0.1), while the allocation to investment trusts sharply decreases (< -0.1), and vice versa (22 observations deleted).
- We drop observations when the change in equity and bond allocation ($d\left(w^{equity}\right)$ or $d\left(w^{bond}\right)$) are missing (100 observations deleted).
- We drop outliers for the change in the equity allocation or bond allocation, which holds for $\frac{abs\left\{d\left(w^{j}\right)-mean\left[d\left(w^{j}\right)\right]\right\}}{3*std[d(w^{j})]} > 1$ (92 observations deleted).

Appendix B. Testing for Unit Roots

Since we have a fixed number of pension funds ($I = 39$) and we assume that pension funds have an infinite horizon ($T \rightarrow \infty$), we apply the Fisher-Dickey-Fuller test for a unit root. To control for time effects, we subtract the cross-sectional means. The model we test, the corresponding hypotheses, and the test results are shown in table B.1, for which we specified six lags. The results are robust for the specification of the number of lags. Hence, we have no evidence to reject the null hypothesis, so we conclude that the panels for the equity and bond allocation contain unit roots.

Table B.1. Fisher-Type Unit-Root Test for w^j Based on Augmented Dickey-Fuller Tests

$d(w^j_{i,t}) = \alpha + \beta d(w^j_{i,t-1})$ H_0: All panels contain unit roots $(\alpha, \beta = 0)$ H_a: At least one panel is stationary $(\alpha, \beta \neq 0)$		
	p-value	
Test	**j = Equity**	**j = Bond**
Inverse χ^2	0.9139	0.9655
Inverse Normal	0.9413	0.9981
Inverse Logit t	0.9424	0.9987
Modified Inverse χ^2	0.9056	0.9546
No Evidence to Reject H_0		

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